Using Learning Style Data in an Introductory Computer Science Course

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1. ABSTRACT
Because learning styles affect how students approach new material, a deeper comprehension of these styles can help professors enhance student learning experiences. In this paper we discuss how learning style data can be used to help guide student study habits and instructional strategies. Additionally, we examine whether or not there is a correlation between learning style and academic performance in an introductory computer science course.

2. INTRODUCTION
A student's learning style indicates how that student responds to a wide range of intellectual and perceptual stimuli and how they prefer to approach new material. For example, some students may prefer to discuss new concepts in small groups, while others may prefer solitary study of those concepts. A student's learning style can therefore be used to guide the student to the study techniques that are most likely to be effective for them.

Learning style data can also be used to help improve instructor presentations. For example, an instructor may have an instructional strategy they use consistently that interferes with a particular learning style, causing students with that learning style to perform less proficiently than other students. This information can then be used to suggest alternative delivery methodologies to the instructor to help them reach those students.

Additionally, research has shown that there is very little relationship between overall college achievement and learning style [6], yet there are some indications that there is a relationship between learning style and performance in specific subject areas. For example, Moldafsky found that learning style could affect an individual's skill in information processing, decision-making attitudes toward computers, and computer anxiety [4]. We therefore hypothesize that learning style may affect student performance in particular courses.

SIGCSE '99 3/99 New Orleans, LA, USA
1-58113-085-6/99/0003...

All students attending the U.S. Air Force Academy (called USAFA hereafter) are required to take an introductory course in computer science (CompSci 110). Because the course is taken by all students in either their freshman or sophomore year, it assumes no prior knowledge about computers. The course has been designed to cover four basic areas of study, but the key topic is problem solving with computers. Since students need to know how to solve problems before they can solve them using computers, we start by helping the students develop their problem solving skills. They then learn how to use these skills to solve problems using computers and the Ada programming language.

Last year, we incorporated the use of learning style data into the course. All students in the course were administered 4 learning style instruments, which we then used in a number of ways. We provided students with a brief description of how to interpret the results of these instruments, and even more importantly, how to use those results to guide their study habits. We performed statistical analyses using this data to help guide instructors toward more effective instructional techniques. Finally, we used the learning style data to test the hypothesis that learning style affected performance in CompSci 110, and found numerous statistically significant results.

The next section describes the experiment in detail. Section 4. discusses our use of learning style data to guide study habits, and Section 5. describes our statistical analysis results for each instructor in the course. Section 6. presents the results of our examination of the correlation between learning style and CompSci 110 performance, and the final section provides our conclusions.

3. EXPERIMENT DESCRIPTION

The learning style data was collected on the 877 students enrolled in CompSci 110 during the Fall 1997 and Spring 1998 semesters; 804 of the students were freshmen, with sophomores comprising the remaining 73 students. It is clearly reasonable to claim that our sample is representative of students in the course, since all the enrolled students were included in the sample.

Four instruments were used to collect the learning styles data: the Group Embedded Figures Test, the Felder Index of Learning Styles, the Kolb Learning Styles Inventory II '85, and the Keirsey Temperament Sorter. Each instrument is discussed in further detail below.

The Group Embedded Figures Test (GEFT) measures field independence and field dependence. Field independent individuals see detail easily, are analytical, prefer to work alone, and can function with very little environmental support. Field dependent individuals are less able to disambiguate information, take learning cues from authority figures, prefer to work in groups, and have excellent communication skills.

In the GEFT, individuals must find a simple embedded geometric figure hidden in a more complex figure. There are 18 complex figures in the GEFT [5]. Students can then be classified in one of four quartiles based on their results, though we simply use the raw scores in our statistical analysis.

Felder's Index of Learning Styles (ILS) measures four different dimensions of an individual's learning style [1]. The four dimensions are active/reflective, sensing/ intuitive, visual/verbal, and sequential/global. Active learners learn better by doing something active - discussing the material, explaining it to someone, or using it to solve problems. Reflective learners learn better by thinking about the material before trying to explain or use it. Sensing learners like to memorize facts and solve problems using well-established methods, while intuitive learners prefer discovering relationships and using innovative problem-solving approaches. Visual learners retain more from things they see - pictures, diagrams, flow charts, etc. Verbal learners get more out of words - written and spoken explanations. Finally, sequential learners gain understanding in linear, logical steps, while global learners tend to learn almost random pieces of material, then suddenly "get it".

Felder's ILS consists of a set of 44 sentences for which individuals select the better of two completions. The instrument provides scores (as 11A, 9A, 7A, 5A, 3A, 1A, 1B, 3B, 5B, 7B, 9B, or 11B) for each of the four dimensions.

Kolb's Learning Styles Inventory II '85 measures an individual's intrinsic learning style or predisposition in any given learning situation [3]. Kolb describes a learning cycle of involvement in concrete experiences (Concrete Experience), followed by observation of and reflection on those experiences (Reflective Observation), followed by integration of those observations into a sound theory (Abstract Conceptualization), followed by use of those theories to make decisions and solve problems (Active Experimentation), leading back to more concrete experiences.

Kolb's instrument consists of a set of 12 sentences for which individuals rank order four completions on a scale of 1 to 4. The instrument provides scores (ranging from 12 to 48) for the individual's predisposition toward Concrete Experience, Reflective Observation, Abstract Conceptualization, and Active Experimentation.

The Keirsey Temperament Sorter is not strictly a learning style instrument; rather, it was designed to identify different personalities [2]. The model used by Keirsey is very similar to Myers-Briggs and other personality models. The four dimensions used by Keirsey are extravert/introvert, intuitor/sensor, thinker/feeler, and judger/perceiver. Extraverts tend to try things out and focus on others, while introverts tend to think things through and focus on ideas. Sensors tend to be practical, detail-oriented, and focus on facts and procedures. Intuitors tend to be imaginative, concept-oriented, and focus on meanings. Thinkers tend to be skeptical and make decisions based on logic and rules, while feelers tend to make decisions based on personal considerations. Judgers tend to set and follow agendas, and seek closure even with incomplete data. Perceivers tend to be more adaptive, and resist closure in the hopes of procuring more data.

Keirsey's Temperament Sorter consists of a set of 70 sentences for which individuals select the better of two completions. Based on the individual's completion choices, their personality is classified in each of the 4 dimensions.

The results of the 4 instruments were provided to the students, and were then used in our statistical analyses.

4. GUIDING STUDY HABITS

One of the uses for our learning style data involves guiding student study habits based on that data. To help provide this guidance, we supply each student with a brief (3 pages) reading that discusses each of the learning style models and relates different learning styles to the approach they should take toward the material in CompSci 110. This information is provided at the beginning of the semester, but it is not repeated or referred to throughout the remainder of the semester. Students can use the learning styles reading in conjunction with their learning styles instrument results to select their study habits appropriately.

Visual and Verbal Learners

Visual learners retain more from things they see - pictures, diagrams, flow charts, etc. Verbal learners get more out of words - written and spoken explanations. If you're a visual learner, it might help to diagram your problem solutions to check them before coding. It could also help if you draw a picture of each Ada construct you learn. If you're a verbal learner, writing the required English algorithm for each problem solution may be sufficient for you to check your work.

Figure 1. Learning Styles Reading Excerpt

For example, one of the dimensions measured by Felder's ILS is the visual/verbal dimension. In Figure 1., we provide the corresponding excerpt from the reading provided to the students. If students find that they tend toward visual learning, they can use this information to help guide their study of Ada constructs. We teach students how to use control flow graphs (a flowchart-like representation) to graphically depict various Ada constructs, such as selection and iteration constructs, and a visual learner might therefore find it easier to use these graphs as they try to understand the constructs. Alternatively, verbal learners may find that using this graphical representation is not particularly helpful. These students may choose to use syntax boxes for the constructs or textual examples to help them understand those constructs.

Students can also use learning style results to determine whether to study in groups or alone. Students classified as extraverts by Keirsey's Temperament Sorter or as field dependent by the GEFT may find it more effective to study in groups, while students classified as introverts or field independent may find it more effective to study individually.

Since the readings include discussions of all the learning styles and their relationship to CompSci 110, we provide students with course-specific guidance on how to use their learning styles results to approach the course material. Though we have not conducted any formal surveys to determine whether or not students actually use this guidance, we believe this to be a valuable use of the learning style data.

5. INSTRUCTOR-SPECIFIC RESULTS

Learning style data can also be used to help instructors improve their instructional techniques. For instance, if an instructor uses an instructional strategy that interferes with a particular learning style, students with that learning style may exhibit poor performance in the course. If analysis of the learning style data indicates this to be true, the instructor can modify their instructional strategies to also reach those students.

To take advantage of this use of the data, for each instructor we performed statistical analysis using the learning style data and course performance data. The learning style data provided our independent variables for this analysis, with the independent variables as follows: GEFT score, Felder scores for the four dimensions (Active/Reflective, Sensing/Intuitive, Visual/Verbal, and Sequential/Global), Kolb scores for the learning cycle (Concrete Experience, Reflective Observation, Abstract Conceptualization, and Active Experimentation), and Keirsey scores for the 4 dimensions (Extravert/Introvert, Intuitor/Sensor, Thinker/Feeler, and Judger/Perceiver).

Course performance data provided the response variables for our analysis. These variables were : Order of Merit in the course (the top student in the course is 1, and so on), Quiz percentage, Lab percentage, Practica (in-class programming exams) percentage, Test percentage, Group Case Study percentage, Final Exam percentage, and final Percentage in the course. We note that all response variables are measured on an interval scale.

Many of the independent variables are also measured on an interval scale. To examine the relationship between the interval independent variables and course performance, we correlated each of these independent variables with each of the response variables discussed above. For each such correlation we calculated Pearson's Correlation Coefficient and a measure of statistical significance (p). The coefficient ranges from -1.0 to 1.0, with a coefficient magnitude close to 1.0 indicating a strong linear relationship and a magnitude close to 0.0 indicating no linear relationship. Correlations found to be statistically significant using the common guideline ($p=0.05$) are reported below; all other correlations were not statistically significant. We point out before continuing that correlation is not a measure of causality; it simply measures the linear relationship between two variables. Additionally, we note that a low correlation only indicates that the variables are not linearly associated; they could still be related in some non-linear way.

The independent variables related to the Keirsey Temperament Sorter are bivariate and unranked (and are therefore measured on a nominal scale). For these independent variables, we performed a standard two-tailed t-test to test the null hypothesis that a particular Keirsey dimension did not affect the mean for each response variable. We again used $p=0.05$ as our limit for statistical significance, with significant results reported below; all other t-tests yielded results that were not statistically significant.

We are, of course, faced with an interesting paradox as we consider the results of our analysis. As researchers, we would like to see many statistically significant results, but as instructors we would rather find that all our instructors have "balanced" teaching so that a student's learning style doesn't have any effect on their course performance.

The dataset includes 24 instructors who taught from 12 to **78** students in the course over the year. Given **13** independent variables and 8 response variables, the maximum number of statistically significant results for any given instructor is 104. Totals for each instructor ranged **from 3** to 38, and we viewed any total of 10 (10% of the maximum) or more statistically significant results as a signal to discuss instructional style with that instructor; 12 out of the 24 instructors had totals of 10 or more.

To see how we can use this information, consider one instructor's results for Felder's Active/Reflective dimension. The correlations for this instructor are positive, relatively strong (0.42 and higher), and statistically significant for 5 of the response variables, indicating that active learners tend to do better in this instructor's class than reflective learners. We can then use this information to suggest that the instructor build more "reflection" time into his lectures, trying to reach a better balance of active group or board work and individual work.

This same technique can be used to discuss the impact of the other statistically significant results for this instructor, as well as other instructors. Although the counts of statistically significant results give us a starting point, we must then consider the strength (and sign) of each correlation or the results of the t-tests to provide appropriate guidance to the instructors. In any case, careful analysis of the learning style and course performance data gives us an excellent opportunity to help guide instructors' teaching strategies so they can more effectively reach a wide range of student learning styles.

6. COURSE-WIDE RESULTS

As researchers, it is also interesting to consider whether or not learning style affects course performance independent of the student's instructor. To examine this idea, we performed course-wide statistical analysis.

Course-wide results for the year are provided in Figure 2. Independent variables are listed along the top of the figure, and each response variable has its own row. Each entry in the table provides the value of the correlation coefficient and its p value in parentheses (or simply the p value in parentheses for t-tests). Only statistically significant results are provided in the table; other entries are left blank.

From the correlations, we see that Kolb's Abstract Conceptualization has the strongest correlation with most of the course performance indicators. The correlation is positive, indicating that a strong predilection for Abstract Conceptualization may predict better performance in this course. The negative coefficient for OM indicates that a higher AC score implies a-lower (better) course standing. The GEFT scores have a positive, though slightly weaker, correlation with all the response variables, indicating that field independent students tend to do better in the course than field dependent students. Felder's Active/Reflective

	GEFT	Felder				Kolb				Keirsey			
		A/R	S/I	V/V	S/G	CE	RO	AC	AE	E/I	I/S	T/F	J/P
Order of Merit	-0.22 (0.00)	-0.14 (0.00)				0.17 (0.00)	0.12 (0.00)	-0.26 (0.00)		(0.01)		(0.00)	(0.02)
Quiz	0.17 (0.00)	0.11 (0.00)		0.10 (0.00)		-0.07 (0.05)	-0.12 (0.00)	0.18 (0.00)				(0.00)	
Labs	0.15 (0.00)	0.07 (0.04)				-0.14 (0.00)	-0.09 (0.01)	0.16 (0.00)	0.07 (0.04)		(0.04)	(0.00)	(0.00)
Practica	0.22 (0.00)	0.10 (0.00)				-0.16 (0.00)		0.19 (0.00)		(0.05)		(0.01)	(0.00)
Tests	0.23 (0.00)	0.16 (0.00)	0.12 (0.00)			-0.12 (0.00)	-0.11 (0.00)	0.24 (0.00)		(0.00)		(0.00)	
Case Study	0.11 (0.00)						-0.10 (0.01)						
Final Exam	0.19 (0.00)	0.16 (0.00)		0.08 (0.03)		-0.15 (0.00)	-0.08 (0.03)	0.29 (0.00)		(0.02)		(0.00)	
Percent	0.22 (0.00)	0.14 (0.00)				-0.16 (0.00)	-0.13 (0.00)	0.26 (0.00)		(0.03)		(0.00)	(0.02)

Figure 2. Course-Wide Results

dimension had a positive correlation with almost all of the response variables, indicating that reflective students tend to do better in the course than active students. The negative correlations for Kolb's Concrete Experience indicate that students with a predilection toward Concrete Experience tend to do worse in the course. Students with a predilection toward Reflective Observation also tend to do worse in the course.

From the t-test results, we note that Keirsey's Extravert/Introvert and Thinking/Feeling dimensions seem to have some impact on numerous measures of course performance. Introverts tend to do better in the course than Extraverts, which is consistent with the results for Felder's Active/Reflective dimension. Thinkers tend to do better in the course than Feelers, which seems intuitive considering the technical nature of the material and the requirement to generate problem solutions using logical thought processes.

It is important to note that there may well be (and probably are) other factors that affected student performance in the course. Other factors that could affect course performance include gender, student class year, and the semester and year in which the course was taken.

7. CONCLUSIONS

Because learning style affects how a student responds to stimuli and approaches new material, there are a number of ways we can use learning style data to enhance that student's learning experience. We can use learning style data to guide the student toward more effective study habits and we can use that data to help instructors in their selection of instructional strategies.

We conducted an experiment on 877 students enrolled in an introductory course in computer science, using 4 different learning style instruments to collect learning style data on those students. We then used this learning style data to recommend suitable study habits for those students. We also evaluated (for each instructor) the impact of the various learning styles on 8 measures of course performance. For half of the instructors, we found a sufficiently large number of statistically significant results to indicate that discussion of instructional strategies is merited; we are currently holding those discussions with the instructors. Finally, we conducted course-wide statistical analysis to determine the impact of learning style on performance in this course, and found numerous statistically significant results.

We are continuing this work with the students currently enrolled in CompSci 110. Administering the learning style instruments takes a reasonably small amount of time (typically an hour or so), and the resulting data can be used to help students develop their study habits, to help instructors select their instructional strategies more effectively, and to help researchers better understand how different learning styles can affect student performance.

8. REFERENCES

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