Learning Styles of Computer Science I Students

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***Abstract*— We conducted a study to investigate how learning styles related to the introductory Computer Science I course: the learning styles of the student population that took the course; course completion rates as they related to learning styles; relationship between the final grade in the course and learning styles; and the correlation between project and assignment completion rates and learning styles. We found that students in the course preferred active, sensing, visual and sequential learning styles. There was no significant difference in the course completion rates along any dimension that could not be explained based on prior preparation. Reflective and intuitive learners earned better grades in the course than active and sensing learners. While male students earned better grades than female students and traditionally represented students earned better grades than underrepresented students, these differences may be attributable to differences in prior preparation. In this context, SAT scores were found to be better predictors of student grades in Computer Science I than high school GPA. Programming projects in the course favored reflective students whereas online assignments favored sensing and sequential learners – unsurprising, since the design of these course instruments were congruent with the definition of these learning styles. It is hoped that this study provides insight into the types of course activities that might be incorporated into Computer Science I to accommodate the different learning styles of students. (*Abstract*)**

Keywords—Online tutors; Felder-Silverman Learning Style Inventory

I. INTRODUCTION

Computer Science I is the introductory course in the Computer Science curriculum. It covers problem-solving and programming. It is technical in nature. It is a required course for Computer Science majors. Currently, it is also being promoted for non-Computer Science majors as a course that inculcates computational thinking, a skill considered essential in 21st century [4].

In the context of *Computer Science I* course, we wanted to investigate the learning styles of the student population; the course completion rates as they related to learning styles; the relationship between the final grade in the course and learning styles; and the correlation between project and assignment completion rates and learning styles.

Computer Science I course as taught by the author is hands-on. Each class begins with a lecture that covers a new topic, followed by a closed laboratory [5] in which students write a program under the supervision of the lecturer. Each week, students are assigned one after-class programming project. In addition, they are also assigned 1-2 after-class online assignments, which are meant to help students learn programming concepts by solving small-scale problems. Finally, assessment in the course is done in terms of two tests and a final. All three are hands-on, open-book, open-notes, in-class, online programming sessions [6] wherein students write, compile and test a program for a given problem statement.

So, the course is not only technical in nature, but also very hands-on. It employs active learning, problem-solving, programming, and epistemic assessment. The course is typically taken by both Computer Science and non-Computer Science majors, the latter including Mathematics, Physical Sciences and non-Science disciplines.

II. DATA COLLECTION AND ANALYSIS

For this study, we collected data over nine semesters from fall 2011 through fall 2016, with some missing semesters in between when the course was not taught by the author. In each of these semesters, we asked students to fill out Felder Learning Styles Inventory [1] as their first after-class assignment in the course. A total of 184 students filled out the survey over those 9 semesters. Students were asked to identify their sex and race. 136 students identified themselves as male and 48 as female. Additional data such as SAT score, high school GPA, and major were also collected from the Office of Institutional Research and collated for this study.

For the purposes of this study, representation was defined based on race: Caucasians and Asians were grouped as traditionally represented, and the other races (Black/African American, Hispanic/Latino, Native Hawaiian/Pacific Islander and Other) were grouped as under-represented [2]. 134 students were traditionally represented, and 34 were from under-represented groups. The remaining students did not identify their race. The course qualified for General Education credit. So, both Computer Science and non-Computer Science majors took the course. In our study, 57 students were declared Computer Science majors, 72 were Math/Other Science majors and 43 were non-Science majors. (The rest were undeclared majors).

Table I shows that the collected data had normal distribution: Kurtosis values are within ± 1.0. Negative values indicate steeper peaks than normal distribution for most measures. The data is also symmetric as indicated by

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skewness values within ± 1.0. Positive skewness on some measures indicates greater number of smaller values and vice versa.

TABLE I. NORMALITY OF COLLECTED DATA

	Kurtosis	Skewness
Active	-0.817	0.018
Reflective	-0.841	0.001
Sensing	-0.693	-0.338
Intuitive	-0.605	0.361
Visual	-0.435	-0.484
Verbal	-0.419	0.507
Sequential	0.026	-0.093
Global	0.050	0.154

A. Learning styles of the population

The learning styles inventory generates two scores for each dimension, corresponding to the two extremes of the dimension, e.g., along the Active-Reflective dimension, each student gets one score for Active and another for Reflective measure. The sum of the two scores on a dimension always adds up to 11. So, a student who shows no preference for either end of a dimension would score 5 / 6 on the two extremes of the dimension. If a population does not have a preference for either extreme on a dimension, its mean score would be 5.5 on both the measures.

Paired samples t-test of active and reflective scores yielded a significant preference [$t(185) = 2.168$, $p = 0.031$) for active (5.84 ± 0.322) over reflective (5.12 ± 0.325). *Students were significantly more active than reflective learners.* Cohen's d for the difference was 0.32. So*, the preference for active over reflective learning was small.* One-way ANOVA of active score with sex and representation as independent factors yielded no significant effect for sex [$F(1,168) = 0.011$, $p = 0.918$] or representation [$F(1,168) = 0.029$, $p = 0.865$].

Paired samples t-test of sensing and intuitive scores yielded a significant preference [$t(185) = 4.658$, $p < 0.001$] for sensing (6.40 ± 0.399) over intuitive (4.52 ± 0.395). *Students were significantly more sensing than intuitive.* Cohen's d for the difference was 0.68. So, *the preference for sensing over intuitive learning was medium.* One-way ANOVA of sensing score with sex and representation as independent factors yielded no significant main effect for representation [$F(1,168) = 0.208$, $p = 0.649$]. The effect for sex was marginally significant [$F(1,168) = 2.896$, $p = 0.091$]: the score of male students was 6.22 ± 0.618 and that for female students was 7.229 ± 0.994. *Female students were marginally more sensing than male students.*

Paired samples t-test of visual and verbal scores yielded a significant preference [$t(185) = 12.555$, $p < 0.001$] for visual (7.57 ± 0.328) over verbal (3.38 ± 0.329). *Students were significantly more visual than verbal learners.* Cohen's d for the difference was 1.84. So*, the preference for visual over verbal learning was huge.* One-way ANOVA of visual score with sex and representation as independent factors yielded no significant main effect for sex [$F(1,168) = 0.169$, $p = 0.682$] or representation [$F(1,168) = 0.539$, $p = 0.464$].

Paired samples t-test of sequential and global scores yielded a significant preference [$t(185) = 7.695$, $p < 0.001$] for sequential (6.55 ± 0.279) over global (4.37 ± 0.281). *Students were significantly more sequential than global learners.* Cohen's d for the difference was 1.12. So*, the preference for sequential over global learning was very large.* One-way ANOVA of sequential score once again yielded no significant main effect for sex [$F(1,168) = 0.006$, $p = 0.936$] or representation [$F(1,168) = 0.787$, $p = 0.376$].

TABLE II. MEAN SCORES ALONG THE FOUR DIMENSOINS

	Mean ± 95% Confidence Interval		
Active	5.84 ± 0.322	5.12 ± 0.325	Reflective
Sensing	6.40 ± 0.399	4.52 ± 0.395	Intuitive
Visual	7.57 ± 0.328	3.38 ± 0.329	Verbal
Sequential	6.55 ± 0.279	4.37 ± 0.281	Global

When we repeated the analysis for Computer Science majors (N=57), we found similar statistically significant preference for active, visual and sequential learning, but no significant preference along sensing-intuitive dimension, as shown in Table III.

TABLE III. MEAN SCORES ALONG THE FOUR DIMENSOINS FOR COMPUTER SCIENCE MAJORS

	Mean ± 95% Confidence Interval		
Active	6.14 ± 0.571	4.86 ± 0.571	Reflective
Sensing	5.63 ± 0.756	5.30 ± 0.757	*Intuitive*
Visual	7.33 ± 0.566	3.67 ± 0.566	Verbal
Sequential	6.56 ± 0.559	4.42 ± 0.564	Global

Similar analysis for non-Computer Science majors (N=115) yielded a significant preference for sensing, visual and sequential learning, but no statistically significant preference along active-reflective dimension, as shown in Table IV.

TABLE IV. MEAN SCORES ALONG THE FOUR DIMENSOINS FOR NON-COMPUTER SCIENCE MAJORS

	Mean ± 95% Confidence Interval		
Active	5.77 ± 0.400	5.17 ± 0.405	*Reflective*
Sensing	6.70 ± 0.488	4.22 ± 0.479	Intuitive

Visual	7.62 ± 0.436	3.30 ± 0.437	Verbal
Sequential	6.49 ± 0.336	4.40 ± 0.339	Global

The difference between Computer Science and non-Computer Science majors was not statistically significant on active score [t(178) = -0.772, p = 0.441]. But, it was statistically significant on sensing score [t(178) = 1.989, p = 0.048]: non-Computer Science majors tended to be significantly more sensing (mean of 6.70 ± 0.488) compared to Computer Science majors (mean of 5.85 ± 0.704).

B. *Course completion rates*

Next, we considered course completion: a student completed the course if the student passed the course with at least a D grade. Students who failed the course or withdrew from it did not complete the course.

Independent samples t-test of course completion comparing active (active score 6 or greater) versus reflective (active score 5 or less) students yielded a significant effect: [t(179) = 2.37, p = 0.019]: *active students seemed to be significantly less likely to complete the course than reflective students*. Table V shows the number of students in each group. Three students who dropped out of the course are not included in the table. The high attrition rate of 38.12% is typical of *Computer Science I* course nationwide [3].

TABLE V. **COMPLETION RATES FOR ACTIVE AND REFLECTIVE STUDENTS**

	Active	Reflective	Total
Did not complete	45	24	69
Completed	53	59	112
Total	98	83	181

However, there was no longer a statistically significant difference in the completion rates of active and reflective students when we re-ran ANCOVA of course completion with active-reflective group as fixed factor and high school GPA as covariate [F(1,136) = 1.583, p = 0.211] or SAT score as co-variate [F(1,132) = 1.559, p = 0.214].

Similar independent samples t-test of course completion did not yield any significant main effect along the other three dimensions:

- Sensing versus intuitive students: [t(179) = 0.247, p = 0.805].
- Visual versus verbal students: [t(179) = 1.158, p = 0.248].
- Sequential versus global students: [t(179) = 1.44, p = 0.152].

So, there was no significant difference in the course completion rates along any dimension that could not be explained based on prior preparation.

C. *Course grades*

Students who completed the course, i.e., those who did not withdraw or fail the course were grouped into two: those who scored A/B grade versus those who scored C/D grade.

Independent samples t-test of active score for these two groups yielded a marginally significant main effect: [t(109) = -1.629, p = 0.106]. *Students who scored C/D grade were marginally more active than those who scored A/B* as shown in Table VI.

TABLE VI. **ACTIVE SCORE BY GRADE EARNED**

Grade	N	Mean ± 95% Confidence Interval
C/D	29	6.17 ± 0.702
A/B	82	5.40 ± 0.492

Conversely, independent samples t-test of final grades of active (active score of 6 or more) and sensing (active score of 5 or less) students yielded a significant main effect for learning style: [t(109) = 2.873), p = 0.005]. *Active students scored significantly lower grades than reflective students* as shown in Table VII. Cohen's d for the difference was 0.54. So, the effect size was medium. For this analysis, Grades A, B, C and D were coded as 1, 2, 3 and 4 respectively. So, the average grade for active learners was a little shy of B, whereas that for reflective learners was between A and B.

ANCOVA of final grades with active-reflective as fixed factor still yielded a significant difference between the groups whether SAT score was used as the covariate [F(1.85) = 7.334, p = 0.008] or high school GPA [F(1,86) = 5.027, p = 0.028]. (The differences in N are due to unavailability of SAT score/high school GPA for some of the students.)

TABLE VII. **FINAL GRADE FOR ACTIVE VERSUS REFLECTIVE LEARNERS**

Style	N	Mean ± 95% Confidence Interval
Active	53	2.13 ± 0.236
Reflective	58	1.66 ± 0.224

Similarly, independent samples t-test of sensing score for these two groups yielded a marginally significant main effect: [t(109) = -1.843, p = 0.068]. *Students who scored C/D were marginally more sensing than those who scored A/B* as shown in Table VIII.

TABLE VIII. **SENSING SCORE BY GRADE EARNED**

Grade	N	Mean ± 95% Confidence Interval
C/D	29	7.21 ± 0.904
A/B	82	6.10 ± 0.624

Conversely, independent samples t-test of final grades of sensing (sensing score of 6 or more) and intuitive (sensing score of 5 or less) students yielded a significant main effect for learning style: [t(109) = 2.034, p = 0.044]. *Sensing students scored significantly lower grades than intuitive students* as shown in Table IX. Cohen's d for the difference was 0.4. So, the effect size was medium. The average grade for sensing students was B, whereas that for intuitive students was between A and B.

ANCOVA of course grade with sensing-intuitive as fixed factor still yielded a significant difference between sensing and intuitive students when high school GPA was used as covariate [F(1,86) = 5.587, p = 0.02], but not when SAT score was used as covariate [F(1,85) = 1.659, p = 0.201].

TABLE IX. **FINAL GRADE FOR SENSING VERSUS INTUITIVE LEARNERS**

Style	N	Mean ± 95% Confidence Interval
Sensing	70	2.01 ± 0.209
Intuitive	41	1.66 ± 0.270

No similar significant effect was found for visual [t(109) = -1.088, p = 0.279] or sequential [t(109) = -0.889, p = 0.376] scores between A/B and C/D grade earners.

Independent samples t-test of the final grades with sex as the fixed factor yielded a significant main effect for sex: [t(109) = -2.564, p = 0.012]. *Male students scored significantly better grades than female students* as shown in Table X. Cohen's d for the difference was 0.54. So, the effect size was medium. We conducted ANCOVA of the final grade with sex as the fixed factor and high school GPA as a covariate. The difference between the sexes was still statistically significant [F(1,86) = 7.621, p = 0.007], suggesting that the difference between the sexes was not attributable to high school preparation, but rather to the introductory Computer Science course, which if true, would be unfortunate. When we repeated the ANCOVA with SAT score as the covariate, though, the difference between the sexes was no longer significant [F(1,85) = 0.374, p = 0.542]. Furthermore, the Pearson correlation between high school GPA and SAT score was low (0.289, p = 0.011). Given the contradictory results for high school GPA and SAT scores, and the low correlation between the two, the only definitive conclusion that we can draw is that *SAT score is a better predictor of course grades in introductory Computer Science than high school GPA.*

TABLE X. **FINAL GRADES BY SEX**

Sex	N	Mean ± 95% Confidence Interval
Male	78	1.74 ± 0.191
Female	33	2.21 ± 0.316

Similar analysis of the final grades by representation yielded a significant main effect for representation: [t(102) = -2.562, p = 0.012]. *Traditionally represented students scored significantly better grades than under-represented students* as shown in Table XI. Cohen's d for the difference was 0.64. So, the effect size was medium. ANCOVA of the final grade with representation as the fixed factor and high school GPA as a covariate once again yielded a significant difference between the racial groups [F(1,79) = 5.167, p = 0.026]. A similar ANCOVA with SAT score as the covariate yielded no significant difference [F(1,78) = 1.491, p = 0.226]. Given the low correlation between high school GPA and SAT score (0.289), once again, it appears, *SAT score is a better predictor of course grades in the introductory Computer Science course than high school GPA.*

TABLE XI. **FINAL GRADES BY REPRESENTATION**

Representation	N	Mean ± 95% Confidence Interval
Traditional	84	1.75 ± 0.190
Under-represented	20	2.30 ± 0.321

D. Project and Assignment Completion Rates

Next, we considered the rates at which students completed projects and assignments in the course. Projects were programs that students had to write, compile and test. 9-11 projects were assigned in a typical semester. Assignments were online exercises in which students were asked to solve problems on programming constructs. Problets (problets.org), a free resource accessible over the web were used for assignments. 9-12 assignments were given out in a typical semester, not including the Felder-Silverman Learning Styles Inventory assignment. Since the total number of projects and assignments varied by semester, we analyzed completion rate rather than the number of projects and assignments completed by the students. Once again, we considered only those students who had completed the course, i.e., those who had not withdrawn or failed the course.

Independent samples t-test of project completion rates of active (active score of 6 or more) and sensing (active score of 5 or less) students yielded a significant main effect [t(109) = -2.203, p = 0.03]. As shown in Table XII, surprisingly, *active learners completed significantly fewer projects than reflective learners.* Cohen's d for the difference was 0.42. So, the effect size was medium.

TABLE XII. **PROJECT COMPLETION RATES FOR ACTIVE VERSUS REFLECTIVE LEARNERS**

Style	N	Mean ± 95% Confidence Interval
Active	53	0.5998 ± 0.0624
Reflective	58	0.6990 ± 0.06217

No similar difference was found for project completion rates along the other three dimensions. One-way ANOVA of project completion rates with sex and racial representation as fixed factors found a significant main effect for racial representation [F(1,103) = 4.865, p = .03]: *traditionally represented students completed significantly more projects than underrepresented students,* as shown in Table XIII. Cohen's d for the difference was 0.58, suggesting a medium effect size. No similar difference was found for the sexes.

TABLE XIII. **PROJECT COMPLETION RATES BY REPRESENTATION**

Representation	N	Mean ± 95% Confidence Interval
Traditional	84	0.671 ± 0.058
Under-represented	20	0.534 ± 0.108

Analysis of assignment completion rates of sensing (sensing score of 6 or more) and intuitive (sensing score of 5 or less) students yielded a significant main effect [t(109) = 2.834, p = 0.005]. As shown in Table XIV, *sensing learners completed significantly more assignments than intuitive learners.* Cohen's d for the difference was 0.56. So, the effect size was medium.

TABLE XIV. **ASSIGNMENT COMPLETION RATES FOR SENSING VS INTUITIVE LEARNERS**

Style	N	Mean ± 95% Confidence Interval
Sensing	70	0.8023 ± 0.0522
Intuitive	41	0.6551 ± 0.0988

Similarly, we found a significant main effect for sequential (sequential score of 6 or more) and global (sequential score of 5 or less) learners [t(109) = 3.761, p < 0.001]: *Sequential learners completed significantly more assignments than global learners,* as shown in Table XV. Cohen's d for the difference was 0.75. So, the effect size was large.

TABLE XV. ASSIGNMENT **COMPLETION RATES FOR SEQUENTIAL VS GLOBAL LEARNERS**

Style	N	Mean ± 95% Confidence Interval
Sequential	72	0.8156 ± 0.0515
Global	39	0.6231 ± 0.0978

No difference was found for assignment completion rates along the other two dimensions of the learning style inventory. One-way ANOVA of assignment completion rates found no significant differences between the sexes and the racial representation groups.

E. *Validity*

Students filled out the Learning Styles Inventory as an after-class assignment, unsupervised and on their own time. Under such conditions, students could be motivated to complete the assignment as quickly as possible, without paying proper attention to the survey instrument. To address this concern, the reliability of the results of the instrument administered under these conditions was calculated. 24 students had filled out the inventory twice. The correlation between the two sets of results for these 24 students was calculated. As shown in Table XVI, the correlations confirmed the reliability of the results of the learning styles inventory as administered online and filled out by students on their own time.

TABLE XVI. **RELIABILITY OF THE RESULTS**

N=24	First Mean	Second Mean	Correlation
Active	5.792	6.167	0.696
Reflective	5.125	4.833	0.696
Sensing	5.833	6.167	0.884
Intuitive	5.125	4.833	0.900
Visual	7.375	7.875	0.812
Verbal	3.583	3.125	0.826
Sequential	6.208	7.000	0.629
Global	4.708	3.958	0.646

III. DISCUSSION

Students were significantly more active than reflective learners, to a small extent. Students were significantly more sensing than intuitive, to a medium extent. Female students were marginally more sensing than male students. Students were significantly more visual than verbal learners, to a huge extent. Students were significantly more sequential than global learners, to a very large extent. *So, students preferred active, sensing, visual and sequential learning styles.* Computer Science majors had no preference along sensing-intuitive dimension whereas non-Computer Science majors had no preference along active-reflective dimension.

There was no significant difference in the course completion rates along any dimension that could not be explained based on prior preparation.

Students who scored C/D grade were marginally more active than those who scored A/B. Active students scored significantly lower grades than reflective students. The effect size was medium. This difference persisted even when prior preparation, i.e., high school GPA and SAT score were taken into account. Students who scored C/D were marginally more sensing than those who scored A/B. Sensing students scored significantly lower grades than intuitive students. The effect size was again, medium. The difference persisted when high school GPA was taken into account, but not when

SAT score was taken into account. *So, the course favored reflective and intuitive learners.*

Male students scored significantly better grades than female students. Traditionally represented students scored significantly better grades than under-represented students. In both the cases, the effect size was medium. Further analysis showed that this difference persisted even after accounting for high school GPA, but not after accounting for SAT scores. The correlation between high school GPA and SAT score was low. *So, SAT score is a better predictor of course grades in the introductory Computer Science course than high school GPA.* SAT scores are standardized across the nation as compared to high school GPA which can vary among high schools. *If SAT score is a better indicator of prior preparation than high school GPA, the differences between the sexes and racial groups observed in introductory Computer Science are simply a result of differences in prior preparation.*

Active learners completed significantly fewer projects than reflective learners. The effect size was medium. Underrepresented students completed significantly fewer projects than traditionally represented students. Once again, the effect size was medium.

Active learners learn by "working with others", whereas reflective learners learn by "working alone" [1]. Since the projects we assigned in the course were all individual (as opposed to group or pair-programming) projects, it is not surprising that reflective learners completed significantly more projects than active learners. It might be interesting to find out whether active learners complete more projects when they are assigned pair programming [7] or group projects. Active learners learn by "trying things out", whereas reflective learners learn by "thinking things through" [1]. Since programming and problem-solving are both design-driven activities rather than trial-and-error activities, once again, programming projects favored reflective learners over active learners.

Sensing learners completed significantly more assignments than intuitive learners. The effect size was medium. Sequential learners completed significantly more assignments than global learners. The effect size was large.

Sensing learners are "concrete, practical, oriented toward facts and procedures" whereas intuitive learners are "conceptual, innovative, oriented toward theories and meanings" [1]. Online assignments dealt with execution of code and evaluation of expressions – concrete, and driven by facts and procedures. Therefore, it is not surprising that sensing learners completed significantly more assignments than intuitive learners. Sequential learners are "linear, orderly, learn in small incremental steps" whereas global learners are "holistic, systems thinkers, learn in large leaps" [1]. The online assignments were designed to learn programming concepts one at a time by solving small-scale problems. So, it is not surprising that sequential learners completed more assignments than global learners.

So, programming projects favored reflective students whereas online assignments favored sensing and sequential learners. Each of these observations is borne out by the definition of those learning styles and the types of activities in the course.

This study was not meant to predict who makes for a better student in *Computer Science I*, so much as analyze the characteristics of students who choose to take the course, do well in it and complete all of its requirements. What we found was that the course as taught by the author catered to the students with learning styles that were congruent with the types of assessment activities included in the course. A benefit of this study is that it can serve as input for a discussion of what other types of activities in the course might accommodate the needs of students with other learning style preferences.

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