Personality Profiles and Learning Styles of Advanced Undergraduate Computer Science Students

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Abstract: The consistent decline of women and minorities in the IT field is concerning, and has been attributed to a variety of reasons. One suggested cause of this decline is that computer science curricula may inadvertently favor white male students because of the structure and presentation of undergraduate courses. This study examines the Myers-Briggs personality types and Felder-Silverman learning styles of advanced undergraduate students in software engineering classes at three universities in the United States so that professors may better understand their students. This study also examines personality and learning style differences between men and women in these classes, as well as differences between ethnic minorities and non-minorities. Using statistical analyses, the study found that, contrary to popular stereotypes, there were equal proportions of extraverts and introverts in the software engineering classes, that the majority of the male students were intuitive learners whereas the female students showed greater proportions of sensing learners, and that the learning styles and personality traits of the male and female students were, in general, similar.

1 Introduction

The common perception of the information technology (IT) workplace is, at best, unfavorable. The popular press, television news, and movies often depict the stereotypical programmer as an introverted, white male figure whose sole preoccupation is the computer in front of him. While such a portrayal may or may not be accurate, the stereotype may have harmful effects in attracting and retaining a diverse set of talented students to IT-related degree programs. Do potential female and ethnic minority students avoid the computer science (CS) major because this stereotype drives them away? Do professors expect students to fill this stereotype? Are female and minority students being lost because of the apparent dominance of the white male in the computer workplace? Already, a recent study based on United States Department of Labor statistics has shown a rapid decline of women and racial minorities in the IT industry over the past decade [9]. To promote a more diverse field, professors and researchers must understand the personal and pedagogical needs of women and minorities in the CS classroom to attract and retain these groups.

Studies at Carnegie-Mellon [12] have suggested that CS curricula are heavily weighted toward individual achievement and personal knowledge, which are traditionally male social structures, and may be unappealing to women. Seminal papers in other engineering disciplines [6, 7] have suggested that the learning styles of engineering students and the teaching styles of engineering instructors are often misaligned. This mismatch may leave students feeling inadequate or incapable of success in their chosen field. A common problem facing CS professors appears to be a general *lack of understanding* of the learning and social needs of women and minorities in CS, and a lack of understanding of the characteristics of CS students in general. If educators understood better the needs of their students, a revised pedagogy may facilitate a wider interest among all genders, ethnicities, and personalities.

The goal of this paper is to formulate an initial understanding of the personality traits and learning styles of advanced undergraduate computer science students. This description of the types of students found in the advanced undergraduate CS curriculum is intended as a starting point for instructors to understand better their own students, and to consider what changes, if any, are needed in their own classrooms to accommodate all types of students. By understanding and fostering greater ethnic and psychological diversity in the classroom, there is hope that this diversity will continue to enrich the workplace.

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In this paper, we present statistics and discussion of the Myers-Briggs personality types [11] and the Felder-Silverman learning styles [6] of 142 students involved in a year-long study conducted at three diverse North Carolina universities. Statistical analyses were performed to characterize the personality traits and learning styles of advanced undergraduate CS students enrolled in software engineering courses. Comparisons were made between the personality traits and learning styles of men and women, as well as between ethnic minorities and non-minorities to determine if any significant differences existed.

The rest of the paper is organized as follows: Section 2 outlines related work, Section 3 describes our research setting and method, Section 4 discusses the Myers-Briggs personality type findings in our study, Section 5 discusses the Felder-Silverman learning styles findings in our study, and we conclude in Section 6.

2 Related work

This section summarizes related empirical studies of Myers-Briggs personality types and Felder-Silverman learning styles.

2.1 Myers-Briggs

The Myers-Briggs personality types [11] have served as a popular means of characterizing personality traits in both the classroom and the workplace. A considerable amount of work has been published on Myers-Briggs personality types (e.g. [8, 13, 14, 17]). The Myers-Briggs scale has four dimensions:

Introvert-Extravert. Introverts are generally reserved and introspective and find it draining to be in large groups, whereas extraverts thrive in a group setting, are outgoing and will try things out.

Sensing-iNtuition. Sensors prefer information gathered through experience and are attentive to details, while intuitors prefer abstract concepts and are bored by details, preferring innovative thoughts instead.

Thinking-Feeling. Thinkers rely on objective rationalization to make decisions and are considered to be impartial, whereas sensors are more likely to make subjective decisions based on personal feelings rather than strict logic.

Judging-Perceiving. Judgers are typically orderly people who prefer rigid structure and planning but may ignore facts that do not fit their plan or structure, whereas perceivers do little planning and work spontaneously but are more open to facts that do not conform to their views.

Some tests (such as the one used in this study) treat each dimension as an ordinal scale with values ranging from -100 to 100, with the negative values corresponding to one category, e.g. introvert, and positive values corresponding to the other category, e.g. extravert. People can be characterized by their Myers-Briggs Type Indicator (MBTI), which is the combination of the different dimensions. For example, someone who is ENTP is classified as extraverted, intuitive, thinking, and perceiving.

A wide body of knowledge is available on the personality types of engineering students in general, e.g. [5, 14-17]. However, there has been relatively little work on the personality types of CS students in particular (with [3] being a notable exception). In general, these studies have suggested that engineering students are tslightly more introverted than extraverted, that there are many more sensors than intuitors, that there are more thinkers than feelers, and that there are more judgers than perceivers.

In a large, multi-unversity study, McCaulley, et al. [14] examined personality types of engineering students with respect to retention and attrition. They found that introverts and thinkers were most likely to stay enrolled in their degree programs until completion, while those that most often left the engineering program were extraverts and perceivers. Felder also examined personality types with respect to performance in several introductory and advanced-level chemical engineering classes [5]. He found that, in terms of course grades, introverts outperformed extraverts, intuitors typically outperformed sensors (except in hands-on, "real-world" classes), thinkers outperformed feelers, and judgers typically outperformed perceivers. Felder's findings are similar to those found in [8, 13, 15]. Felder hypothesized that students with these personality types outperform their counterparts because these personality types align more closely with professors' teaching styles. A focus on individual assignments favors introverts, intuitors thrive since most professors begin with abstract concepts rather than practical, hands-on application, thinkers prevail in a classroom that requires rational, logical thinking, and judgers are more in line with a well-structured and orderly syllabus.

2.2 Learning styles

The Felder-Silverman learning styles have been used to help students understand their own learning needs and to help professors better tailor their courses to different types of students [6]. The purpose of these learning styles is to help characterize the way in which students absorb and retain information. The Felder-Silverman scale has four dimensions:

Active-Reflective. Similar to extraverts and introverts, active learners learn best by trying things out and working with others, while reflective learners learn more by thinking things out on their own.

Sensing-intUitive. The sensing-intuitive dimension is intended to be the same as in the Myers-Briggs scale.

Visual-verBal. Visual learners absorb information best through pictures, graphs, and charts, whereas verbal learners prefer written or spoken explanations.

seQuential-Global. Sequential students learn in orderly, incremental steps with one point or fact connecting to the next, whereas global learners typically have trouble learning fact-by-fact and learn in large steps after accumulating all the facts.

The test used in this study is based on an ordinal scale for each dimension ranging from -11 to 11 in increments of two (i.e. -11, -9, -7…11). As with the MBTI, a person can be characterized as the combination of their dimensions, e.g. an ASVQ person is an active, sensing, visual, sequential learner.

Several studies have been published outlining the overall distributions of learning styles of engineering students. Typically, there are more active than reflective learners, more sensors than intuitors, a clear majority of visual learners over verbal learners, and more sequential than global learners [1, 2, 7, 10, 18-20]. The characteristics of the distribution varies between institution and subjects.

Some work has been done on the learning styles of CS students in particular. Thomas, et al. [18] examined the learning styles of 107 introductory CS students. They found that there were slightly more active than reflective learners, a clear majority of visual learners over verbal, and equal proportions of sensing or intuitive and sequential or global learners. Thomas, et al. also found that reflective learners typically outperform active learners and verbal learners outperform visual learners with respect to exam grades and course grades [18]. Similar learning style distributions and course performance records were found by Allert [1]. As with introverts and extraverts, reflective learners may have an advantage in classrooms that typically promote individual assignments rather than group work. Felder [6] comments that verbal learners may have an advantage in most classrooms, which focus on oral lectures and presentations filled with lists and bulleted items.

3 Research setting and method

In this section, we describe the students and classes used in the study and our data analysis methods.

3.1 Subject description

The study involved students from undergraduate software engineering courses at North Carolina State University (NCSU)[3], North Carolina Agricultural and Technical State University (NC A&T)[4], and Meredith College[5] during the Fall 2004 and Spring 2005 semesters. NCSU is a large public university, Meredith College is a private women's college, and NCA&T is an official Historically Black College and University (HBCU). A summary of the college and CS department profiles is presented in Table 1.

Table 1 – Institution and CS department profiles

Institution	Total Undergrad Enrollment	Total Minority %	Total Women %	CS Enrollment	CS Minority %	CS Women %
NCSU	21,134	13.0%	43.6%	689	12.2%	10.9%
NCA&T	9,121	93.3%	53.1%	246	92.7%	30.9%
Meredith	2,008	12.0%	99.0%	10*	10%*	100.0%

* values estimated.

The NCSU software engineering classes were predominantly white male with approximately 10% ethnic minorities[6]. The Meredith College class was an all-female class with a variety of ethnic backgrounds. Finally, the

[3] http://www.ncsu.edu
[4] http://www.ncat.edu
[5] http://www.meredith.edu
[6] For this study, we consider ethnic minorities to be African-American, Hispanic, and American Indian. Asian and international students are not considered minority students in this study.

NC A&T students are all African-American students, approximately 60% of whom are male and 40% of whom are female. All of the software engineering courses appeared as a junior-senior level course in each institution's curriculum. The sampling information for these classes is summarized in Tables 2 and 3.

Table 2 – Gender distributions[7] of advanced undergraduate CS students

Institution	Total	Female	Male
NCSU - Fall 2004	68 (100%)	7 (10.3%)	61 (89.7%)
NCSU - Spring 2005	60 (100%)	2 (3.3%)	58 (96.7%)
NCA&T – Spring 2005	9 (100%)	4 (44.4%)	5 (55.6%)
Meredith - Spring 2005	5 (100%)	5 (100%)	0 (100%)

Table 3 – Ethnic distributions[8] of advanced undergraduate CS students

Institution	Total	White	African-American	American Indian	Hispanic
NCSU - Fall 2004	44	36	1	1	1
NCSU - Spring 2005	N/A	N/A	N/A	N/A	N/A
NCA&T - Spring 2005	9	0	9	0	0
Meredith - Spring 2005	N/A	N/A	N/A	N/A	N/A

3.2 Data collection and analysis

The data samples were gathered via an online peer evaluation tool, PairEval[9]. At the beginning of each semester, the students were assigned to take an online MBTI test[10] and an online Felder-Silverman learning style (LS) test[11] via the tool. Though these activities were assigned, they were not compulsory and did not affect student grades. The results of the MBTI and LS tests were recorded by the students in the PairEval tool, wherein the results were logged with their student IDs. The students reported both their MBTI and LS categories (e.g., INTJ, RUVG) and their weighting for the categorical values (e.g. a value of 77% Extravert or a 95% Visual learner).

The sample data were analyzed using the SAS statistical package[12]. The MBTI and LS tests each report their results on an ordinal scale. Dichotomous categories were also created for each of the ordinal scales. Additional data collected, such as gender and ethnic minority information, were reported as categorical variables. Non-parametric tests were conducted on all data collected. The Chi-Squared[13] test was used to test for association when comparing two sets of dichotomous variables. The Wilcoxon-Mann-Whitney test was used when comparing a set of dichotomous variables against a set of ordinal variables. Since none of the effects we investigated showed significant differences across semesters, the data from Fall 2004 and Spring 2005 were pooled. We note that due to small sample size, it is difficult to ascertain the degree to which gender, ethnicity and institute impacted the results.

3.3 Limitations

The small sample size of women and ethnic minorities in this study may impact the accuracy of the statistical tests. Accumulation of further data samples should help alleviate this problem. The actual MBTI and LS values used for data analysis were reported by the students themselves and the tests were not taken under observation, thus the accuracy of the data cannot be guaranteed. The reliability of the MBTI test used in this study is unknown and was chosen because the abbreviated version of the MBTI test was more likely to draw reliable student participation. The LS test has been demonstrated and consistent and reliable [7]. Finally, though the sensing-intuitive dimension is supposed to be equivalent on both scales, we find that the results were not consistent

[7] The gender of each student was inferred from the student's name and may have limited accuracy.
[8] Ethnic information was gathered only from students who completed an Institutional Review Board consent form. Some Spring 2005 information is not available because consent forms were not distributed.
[9] http://agile.csc.ncsu.edu/wiki/doku.php?id=tools#paireval
[10] http://www.humanmetrics.com/cgi-win/JTypes2.asp
[11] http://www.engr.ncsu.edu/learningstyles/ilsweb.html
[12] http://www.sas.com/technologies/analytics/statistics/index.html
[13] A p-value of 0.05 was used for all statistical tests.

across both scales. Both tests produced similarly shaped distributions, though the MBTI test was shifted toward the intuition end of the scale while the LS test was more symmetric about the scale median.

4 Myers-Briggs personality types

We present the MBTI distributions from all three schools in a combined form. Table 4 shows the categorical breakdown of the MBTI for the students in this study, and Table 5 shows the distribution of the MBTI types. These tables are discussed below. The implications of these findings are discussed in Section 4.3.

Table 4 – MBTI categorical breakdown

Myers-Briggs Type	Abbreviation	N	Percentage
Extraversion	E	64	45.07%
Introversion	I	78	54.93%
Sensing	S	42	29.58%
Intuition	N	100	70.42%
Thinking	T	110	77.46%
Feeling	F	32	22.54%
Judging	J	109	76.76%
Perceiving	P	33	23.24%

Table 5 – MBTI distribution

MBTI	N	Percentage	MBTI	N	Percentage
ENFJ	9	6.34%	INFJ	7	4.93%
ENFP	3	2.11%	INFP	1	0.70%
ENTJ	26	18.31%	INTJ	34	23.94%
ENTP	4	2.82%	INTP	16	11.27%
ESFJ	6	4.23%	ISFJ	5	3.52%
ESTJ	14	9.86%	ISTJ	8	5.63%
ESTP	2	1.41%	ISTP	6	4.23%
ESFP	0	0.0%	ISFP	1	0.70%

4.1 Discussion

There are almost even proportions of extraverts and introverts among the students, contrary to the popular notion that computer scientists are antisocial or more inclined to be solitary in nature. Yet, these classes have demonstrated that there are equal portions of reserved students and those who are energized and positively impacted by group work and social interactions. Stronger inclinations are seen in the other categories. In this sample, intuitors, thinkers, and judgers tend to dominate.

The pooled data was compared to other published Myers-Briggs personality type studies. In general, this sample exhibits similar categorical distribution when compared to other studies of engineering students [3, 5, 14-17]; the extravert-introvert category is approximately equally proportionate, there is a clear majority of thinkers over feelers, and there is a clear majority of judgers over perceivers. However, the sample in this study differs from other studies in the sensing-intuition category. While other studies of engineering students report equal proportions or a majority of sensors [5, 14-17], this study shows a clear majority of intuitors.

Intuitors typically are imaginative and concept-oriented and internalize information through their own thought processes. Sensors are the opposite of intuitors, preferring instead details, procedures, and practice as a means of absorbing information. When the majority of students are intuitors, courses that are oriented around procedures and details may prove challenging and/or uninteresting. Thus, that the majority of the students in this sample are intuitors is interesting in a field where much emphasis is placed in the introductory courses on technical details, such as understanding syntax and semantics. The students in our study deviate from another study of CS students in a software engineering class that showed a clear majority of sensors over intuitors [3].

4.2 *Women and minority personality types*

This study also investigated the personality types of women and minorities to determine if there were any observable differences between these groups and those of white males. The sample size of ethnic minorities in our study was too small (n=12) to perform any statistical analyses for comparison between individual ethnic minority groups or to the non-minority group. The results from the ethnic minority students in our study are, in general, too varied to characterize their Myers-Briggs types.

Comparing male and female personality types in this study revealed one statistically significant difference: the sensing-intuition dimension differed between men and women. Men responded as 73% intuition and 27% sensing, while the women were 50% intuition and 50% sensing. This statistically significant difference was also seen in the actual values of the two categories. This is further discussed below.

4.3 *Implications*

Most instructors teach in a style that suits intuitors [6] by emphasizing concepts through lectures and presentations, as opposed to an experienced-based, hands-on approach that is suitable to sensors. Other studies have shown that CS students in particular [3] and engineering students in general [14-16] are typically sensors. However, the majority of the male students in this study are intuitors. Perhaps, the sensors were disenfranchised early in the curriculum. Conceivably, upper-level CS courses, which typically are more theoretical, appeal to intuitors more. That there are more intuitors than sensors in this study is somewhat contradictory to other published sources and bears further investigation. If the teaching styles of instructors favor intuitors, women may be underserved since they are evenly split along the sensing-intuition dimension. Clearly, a balanced teaching style is needed – one that appeals to both the abstract interpretation and innovation of intuitors, and the practical, hands-on experience needs of sensors.

This study also supports other findings [3] that CS students tend to be near equal portions of introverts and extraverts. While many instructional methods reward individual progress through assignments and exams, the focus on the individual may be to the detriment of the extraverts. Based on current stereotypes, many people may be led to believe that all professional computer scientists are isolationists. Yet, the IT profession is dominated by group discussions, meetings, and collaborations among team members. A survey conducted by the third author of this paper polled 320 professional programmers and found that they spent approximately 60% of their days working alone. The remaining 40% of the time was spent either working directly with one other person or in a group. Thus, instructors, to better prepare students for a professional career and to expose them to a more accurate portrayal of their future jobs, should place some emphasis on interpersonal communication. Tailoring courses to the isolated, reserved stereotype will likely drive away valuable and influential members of a field that is already lacking diversity.

5 Felder-Silverman learning styles

The Felder-Silverman LS data have also been aggregated amongst the three schools. The categorical breakdown of the data is shown in Table 6, and the overall distribution of learning styles is found in Table 7. These tables are discussed below. The implications of these findings are discussed in Section 5.3.

Table 6 – LS categorical breakdown

Learning Style Type	Abbreviation	N	Percentage
Active	A	66	46.48%
Reflective	R	76	53.52%
Sensing	S	82	57.75%
Intuitive	U	60	42.25%
Visual	V	115	80.99%
Verbal	B	27	19.01%
Sequential	Q	87	61.27%
Global	G	55	38.73%

Table 7 – LS distribution

LS	N	Percentage	LS	N	Percentage
ASVG	8	5.63%	RSVG	8	5.63%
ASVQ	27	19.01%	RSVQ	21	14.79%
ASBG	1	0.70%	RSBG	5	3.52%
ASBQ	4	2.82%	RSBQ	8	5.63%
AUVG	10	7.05%	RUVG	20	14.09%
AUVQ	13	9.17%	RUVQ	8	5.63%
AUBG	0	0.0%	RUBG	3	2.11%
AUBQ	3	2.11%	RUBQ	3	2.11%

5.1 Discussion

The student learning style distributions in this paper are consistent with other published studies in some respects, but deviates in others. Studies of engineering students conducted by Zywno [19, 20], Kuri and Truzzi [10], and Thomas, et al. [18] show a tendency for the students to be slightly more active learners than reflective. Our findings suggest that the students are slightly more reflective than active; these findings are similar to that of Allert [1] and Buxeda, et al. [2]. Regarding the sensing-intuitive dimension, the mild inclination of the students to be sensors, and their strong inclination to be visual learners on the visual-verbal dimension are consistent with other studies. The sequential-global dimension is difficult to interpret. In published studies, students favor sequential learning but to differing degrees, ranging from 51% to 75%. Our study finds that approximately 61% of the students tend to be sequential learners.

The sensing and intuitive distributions in the learning styles are nearly opposite their distribution in the MBTIs (discussed in section 3.3). One statistically significant difference arose between the Fall 2004 and Spring 2005 distributions. In the Fall 2004 semester, the group was approximately 18% sensors, while the Spring group was approximately 40% sensors. The cause of the change in the sample distribution is unclear.

5.2 Women and minority learning styles

A goal of this study is to determine if significant differences exist between the learning styles of white males and of women and minoritiess. The sample size of ethnic minorities in our study was too small (n=12) to perform any statistical analyses for comparison between individual ethnic minority groups. Additionally, when classified as a single group, ethnic minority participants did not significantly differ in their FS learning styles from their non-minority counterparts.

Comparing male and female personality types in this sample revealed one statistically significant difference: the FS learning-styles sensing-intuitive dimension differed between men and women. Men responded as 54% intuitive and 46% sensing, while the women were 17% intuitive and 83% sensing. This statistically significant difference is also seen in the values of the two categories, which can be seen in Figure 1. The men are evenly distributed about the median, while the women are distributed mostly toward the sensing side of the scale.

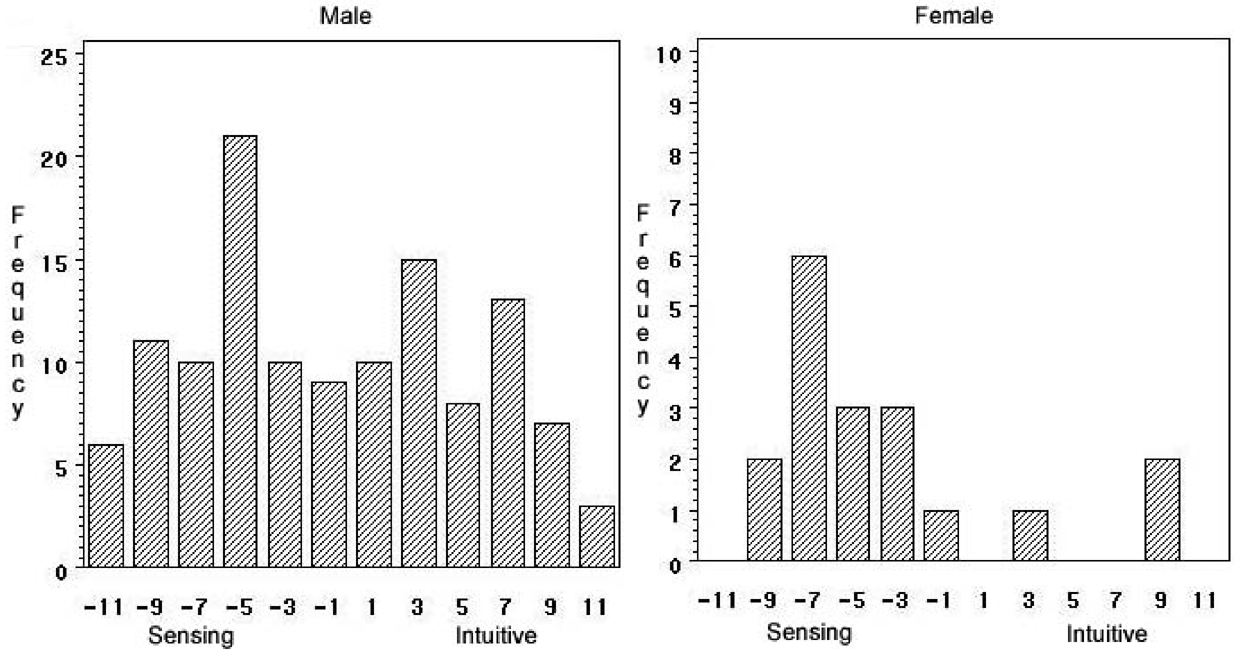

Figure 1: Sensing-Intuitive distribution for men and women.

5.3 Implications

The clear dominance of visual learners in this study is worth noting. Visual learners absorb information best when it is illustrated using diagrams, charts, pictures, etc. However, as Felder points out [6], most classrooms are oriented toward verbal learners in the form of oral lectures and written text either on the board or in lecture notes. This may be particularly true for the CS curriculum, which typically places an emphasis on learning programming language constructs, syntax, and semantics during the first years.

As with the Myers-Briggs sensing-intuitive dimension, we see a difference between men and women. In the learning styles test, the women demonstrated a clear preference toward the sensing end of the scale. As discussed previously, most classrooms are considered to favor intuitors, and thus the disparity between the teaching styles of instructors and the learning styles of women may be a major problem.

6 Conclusion and future work

We highlight several points from our study. We emphasize the similar proportions of introverts and extraverts as shown by the Myers-Briggs personality test. Learning environments should nurture both the outgoing, interactive nature of extraverts, and the reserved, contemplative nature of introverts. Teachers in the CS curriculum can create such an environment by promoting group work and interaction in addition to individual assignments and exams. This approach will not only to appeal to both personality types, but also to provide a more accurate portrayal of the social setting of professional computer programming.

The students demonstrated one significant difference between men and women in this study. In both the MBTI and LS tests, the female responses were more skewed toward the sensing end of the sensing-intuitive scale than their male counterparts. As Felder asserts [6], most classrooms are oriented toward the intuitive learner. This may create a potential disadvantage for women. While a balanced teaching style is necessitated in any case, creating a classroom environment that caters to both sensors and intuitors may be an important step in increasing the retention of women in the CS curriculum and in the CS profession. To appeal to sensors, professors should provide adequate time for hands on exercises with practical problems along with the concept-oriented lectures that appeal to intuitors. We are currently experimenting with teaching agile [4] software development methods in the software engineering classroom. These methods a built upon strong interpersonal communication with active software development and tangible progress, which should appeal the extraverts and sensors in the classroom while also providing material that is favorable to introverts and intuitors.

The students also demonstrated similarities between the women and men in our study. Further sampling is needed, yet these early results suggest that teachers do not necessarily need to adjust their teaching styles to specifically accommodate their female students, except possibly for the sensing-intuitive dimension. The similarities in the learning styles of all students in our sample may be due to students with different learning styles having already been discouraged from the curriculum by the teaching styles of professors in their introductory courses.

Our findings bear further investigation. We are currently examining relationships between learning styles, personality types and student performance in the classroom. Further studies with more software engineering classes in the coming year will yield a larger sample of women and minorities for comparison. We also plan to extend this research to introductory CS courses to monitor personality types and learning styles of students who stay in and leave the program. Our hope is that this and future work will enable the CS community to better understand the challenges facing women and minorities in the curriculum, and to improve the retention of these groups to promote a more diverse and successful field.

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