AC 2008-194: RELATIONSHIP BETWEEN LEARNING STYLE PREFERENCES AND INSTRUCTIONAL TECHNOLOGY USAGE

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Relationship between Learning Style Preferences and Instructional Technology Usage

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Abstract
We have been studying engineering students' learning in both undergraduate and graduate courses on probability and statistics as part of the biomedical engineering curriculum. These courses employ a scaffold of multiple instructional technologies including the course management system, BlackBoard®, hyperlinked PowerPoint® notes, Classroom Performance System (CPS) technology, and "real-world" MATLAB®-intensive problems. The goal of this study is to determine if students with different learning styles (*e.g.,* active vs. reflective learners) have different usage patterns of and derive different benefits from the instructional technologies. We also compare the learning styles of this sample of biomedical engineering students to the existing literature and explore if there are relationships between factors such as learning style, grades and graduate vs. undergraduate status. We present an analysis of Learning Styles Inventory data, survey data on instructional technology perceptions, usage statistics collected from the course management system, and outcome data. In addition, we provide suggestions on how to align instructional strategies (such as interactions between students and interaction with professor) with learning preferences.

I. Introduction

Background

The expanding range of learning technologies has created many choices for instructional delivery. Furthermore for the last decade or so, pedagogy and not technology has captured our attention. "What's different this time, however, is that the focus of change efforts is less on building new institutional structures, redefining the curriculum, or expanding access, and more on the heart of higher education – the teaching/learning process[1]." Our usage of instructional technologies include Blackboard®, a Web-based course management system used at The University of Texas at Austin that is available for any course, Classroom Performance System (CPS) technology that consists of student-operated remote controls and a receiver that records responses to multiple-choice questions posed by the instructor, PowerPoint®, a presentation software package that comes with Microsoft Office and MATLAB®, a high-level technical computing language and interactive environment for algorithm development, data visualization, data analysis, and numerical computation.

In this paper, we build upon our previous studies on how instructional technologies influence students in developing basic content understanding, but also in the development of critical thinking and reasoning skills (as categorized by an educational taxonomy)[2,3]. We found that instructional technologies can provide scaffolds to support different levels of learning. This finding prompted us to question more. Do students learning styles influence their usage of technology and the benefits they derive from it? We know that a one-size-fits-all curriculum has

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limitations and therefore should we assume that a one-size fits-all approach with instructional technologies is not the best approach when it comes to student needs?

Learning styles are our preferences in how we take in and process information. We all recognize there are learning differences and that learners bring their own approach and interests to learning. There are many ways to take in information and process thinking. For some people, a connection is needed while others are more divergent. Others need to see the big picture before any details are provided. Verbalizing ideas is necessary for some while others need private time to think. In order to assess these learning approaches, a number of learning styles inventories exist. The Felder-Solomon Index of Learning Styles (ILS) is frequently used in engineering and was used in this study. Specifics about this index will follow in a later section.

Research on learning styles and technology indicates that students' performance using technology is related to learning style preferences [4]. Care has to be taken to investigate the simultaneous effects of multiple influences of technology and nontechnology factors on learning outcomes. One study found that in contrast to previous studies that examined technology in isolation, when analyzed relative to other learning factors, technology's influence is secondary[5]. Our study, however, does not isolate the use of technology and instead looks at its use across the curriculum and with various measures.

This paper is a study that covers multiple semesters of two statistics courses. Our previous studies included students in BME 335 a core undergraduate course in Biomedical Engineering at The University of Texas at Austin (UT Austin). Generally students in this class are sophomores and many have taken a high school level statistics course. A program outcome for the UT Austin BME program is that our graduates will be able to "design and conduct experiments and analyze and interpret data to support the understanding of biological systems and processes." Similarly, BME graduate students must take BME 380J.5 Biostatistics, Study Design, and Research Methods. This course is to provide students with the proper background and experience to use common hypothesis tests, including tests associated with methods such as regression and ANOVA, and to use common computational statistical methods, such as cluster analysis. Both the undergraduate and graduate courses emphasis practical skills and require students use MATLAB®.

Instructional Technologies

The course management software, Blackboard® is provided for all UT Austin courses. In both the undergraduate and graduate BME statistics course it is used to augment a face-to-face class as a place to post all class lectures, quizzes, discussion forums, emails, a gradebook, and course announcements. Students are familiar with the common look and feel of Blackboard® and often expect its usage in their classes.

Class notes were created in PowerPoint®, the ubiquitous presentation software. While PowerPoint® presentations effectively present charts and graphs and other audio and visual information, they are often relegated to bulleted lists. Such text-based types of presentations seldom engage learners and they certainly do not promote active learning. With the use of hyperlinks, however, the linear aspect of a PowerPoint® presentation is diminished for through a link you can go to another slide besides the next one in the presentation, a different presentation

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altogether, a non-PowerPoint document, or even a Web page. A hyperlinked PowerPoint® presentation has built in flexibility and lectures can be used to promote active learning.

Student interaction and feedback were gathered using CPS (Classroom Performance System) in the undergraduate classes. CPS consists of unique remotes for each student and a receiver that records responses. When the instructor initiates a multiple choice question, the students key in their answers, the results are saved in a data file, and the instructor can display a histogram of class results. Individual and aggregate data are saved for each session.

In order to have students solve real-world problems, they need a tool to perform computationally intensive problems. MATLAB® was selected because it is a high-level language with an interactive environment that is used across the engineering curriculum. Its key features include:

- High-level language for technical computing
- Development environment for managing code, files, and data
- Interactive tools for iterative exploration, design, and problem solving
- Mathematical functions for linear algebra, statistics, Fourier analysis, filtering, optimization, and numerical integration
- 2D and 3DS functions for visualizing data
- Tools for building custom graphical user interfaces

Functions for integrating MATLAB® based algorithms with external applications and languages, such as C, C++, Java, COM, and Microsoft Excel®[6].

Felder Learning Style Model

We administered a Web-based, self-scoring learning styles inventory called the Felder-Solomon Learning Styles Index (ILS) standard questionnaire. Learning styles are not fixed personality traits, but are the results of unique individual programming[7]. Self-report instruments are used to measure learning styles preferences. The Felder model, specifically designed for engineering students, looks at aspects of learning styles in engineering education and based on student results, advocates incorporating active, experiential, collaborative, and student–centered approaches[8]. The dimensions are as follows:

- Sensing learners (concrete, practical) or intuitive learners (conceptual, innovative)
- Visual learners (graphics, pictures, diagrams, etc) or verbal learners (written descriptions)
- Inductive learners (presentations from the specific to general) or deductive learners (presentations from general to the specific)
- Active learners (learn by doing and with others) or reflective learners (learn by thinking thoroughly and alone)
- Sequential learners (linear, learn in small steps) or global learners (systems thinkers, learn in large leaps)

BME students responded to the self-report online ILS to obtain their learning styles scores in the four categories.

Perceptions on Instructional Technology

Little is known about students' perceptions of how instructional technologies influence their educational experience and learning. Yet their attitudes and perceptions must be considered in

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the use of instructional technology if the end result is to have the technology enhance their learning. In order to investigate student perceptions in these areas: general attitudes about learning; reactions to their experiences with technologies in the classroom; and faculty use of technology, an online survey was administered to the students.

2. Methods

These courses integrate instructional technologies across the curriculum and we used several measures to help assess effectiveness. Student participation in the study was voluntary. Given that these classes are intact groups, we could not control for selection bias and we had to allow for students to opt out of participation. Since people who volunteer for a study may be different in some respects from non-volunteers this could have been another source of bias. All of the students in these classes, however, did participate. The ILS questionnaire, consisting of 44 questions, is available on the Web. The completed questionnaires are scored online and responses were collected. Each student was aware of their individual preferences, but for this study, we did statistical analysis comparing the sample of student sample populations.

At the beginning and end of the undergraduate courses, students completed a survey that included both scaled and open-ended questions designed to assess their pedagogical experiences with instructional technologies. All of the students involved in this study responded to a basic demographic survey.

Whenever a student accesses Blackboard® an internal course statistics tool tracks the number of hits. We are able to see which sections of the course were accessed by whom and when. The course statistics can reveal such specifics on an individual student or can produce aggregate statistics for an entire class. Not only can you find out the features accessed, but you can also find out which days and time of the week had the most hits.

Our questions include:
1) Do our BME students' learning styles reflect those of other engineering student populations?
2) Do undergraduate and graduate BME students have similar learning styles?
3) Do students' learning styles impact their preference for different instructional technologies?

To address these questions, we gathered students' ILS scores, student responses to the instructional technology survey, and reviewed the number of hits to the course Blackboard® site.

3. Results and Discussion

1) <u>Do our BME students' learning styles reflect those of other engineering student populations</u>
Data were collected over seven semesters from spring 2004 through fall 2007 (Table 1; data not available for spring 2006). The Learning Styles Inventory was used routinely in the courses to assist students, so these data were available for the majority of students over this time period (84%). A notable demographic difference between this study population and many other studies of engineering students is the large percentage of women in this sample (41%). As is often the case, both our undergraduate and graduate BME majors have a substantially higher percentage of female students than is typically seen in other engineering disciplines.

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Table 1 *Data set summary.*

Semester	Level	Enrollment	LSI (% of enrollment)	% Women
2004 Spring	Graduate	20	19 (95%)	63%
2004 Fall	Undergraduate	21	17 (81%)	29%
2005 Spring	Graduate	21	20 (95%)	30%
2005 Fall	Undergraduate	59	57 (97%)	44%
2006 Fall	Undergraduate	39	26 (67%)	39%
2007 Spring	Graduate	35	35 (100%)	31%
2007 Fall	Graduate	22	21 (95%)	52%
	Graduate	124	95 (77%)	42%
	Undergraduate	119	110 (92%)	40%
	Total	243	205 (84%)	41%

While some variability in median learning style preferences across semesters is inevitable, no substantial trends across semesters were seen in our data (Table 2). Thus, in our analyses we pooled data from across all the semesters.

Table 2 *Learning Style Distributions of UT Austin BME Students.*

Semester	Active (-) to Reflective (+) (Median +/- stdev.)	Sensing (-) to Intuitive (+) (Median +/- stdev.)	Visual (-) to Verbal (+) (Median +/- stdev.)	Sequential (-) to Global (+) (Median +/- stdev.)
2004 Spring	-1.0 +/- 4.7	-1.0 +/- 5.2	-3.0 +/- 4.7	3.0 +/- 5.5
2004 Fall	-1.0 +/- 4.9	-1.0 +/- 5.2	-3.0 +/- 5.0	-1.0 +/-5.6
2005 Spring	0.0 +/- 4.8	-3.0 +/- 5.7	-5.0 +/- 5.5	-1.0 +/- 5.6
2005 Fall	-1.0 +/- 4.5	-3.0 +/- 5.2	-5.0 +/- 3.8	-1.0 +/- 3.9
2006 Fall	1.0 +/- 3.5	-3.0 +/- 5.4	-6.0 +/- 4.5	-1.0 +/- 4.5
2007 Spring	-1.0 +/- 4.9	-5.0 +/- 4.5	-5.0 +/- 4.5	-1.0 +/- 4.2
2007 Fall	1.0 +/- 4.5	1.0 +/- 5.7	-7.0 +/- 3.3	-1.0 +/- 4.4
ALL	*1.0 +/- 4.5*	*-1.0 +/- 5.3*	*-5.0 +/- 4.4*	*-1.0 +/- 4.6*

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Previous studies have reported that the four learning styles dimensions are relatively uncorrelated, with the exception of the sensing/intuitive and sequential/global dimensions. Using data from all semesters combined, we computed the Spearman rank correlation coefficient for each pair of learning styles dimensions (Table 3). Our findings are mostly consistent with prior reports; the only notable correlation was between the sensing /intuitive and sequential/global dimensions (Spearman rho = 0.36, compared to .032 to .055 in the literature) [8]. The observed correlation, however, between the verbal and sequential styles (Spearman rho = -0.27) is higher than previously reported (Pearson rho = -0.09 to 0.07) [8] and may warrant further study. As discussed by Felder some authors have suggested theoretical reasons for a link between the verbal and sequential styles[9].

Table 3 *Correlations between learning style dimensions*

	Active Reflective	Sensing Intuitive	Visual Verbal	Sequential Global
Active Reflective		0.13	0.03	0.15
Sensing Intuitive			-0.01	0.36
Visual Verbal				-0.27
Sequential Global				

Overall, on average our study population has a weak preference for active, sensing, and sequential styles and a moderately strong preference for a visual style. As alternative analysis, we computed the percentage of the students that had strong preferences, defined as a ±9 or ±11 on a dimension. By this measure, our sample has similar percentages of the extremes of active (2%) vs. reflective (4%), sensing (12%) vs. intuitive (6%), and sequential (7%) vs. global (2%) learners. In comparison, 28% of our students had a strong preference for a visual style while none had a strong preference for a verbal style.

Learning style preferences are often similar across students in the same discipline. Felder's research indicates that engineering students overall tend to be active, sensing, visual, and sequential. A study of BME students at another institution reported that the learning styles of their BME students are generally consistent with Felder's findings except in the sequential/global domain for their students were a globally oriented population[10]. As in our analysis, previous studies report that many engineering students have a strong preference for a visual style.

2) Do undergraduate and graduate BME students have similar learning styles?

As discussed above, most reports indicate that engineering students overall tend to be active, sensing, visual, and sequential. Engineering faculty tend to be more reflective, intuitive, and sequential than their students[11]. There is empirical support that graduate students' learning style preferences are more similar to those of faculty than of undergraduate students[12]. Our findings do not align with that evidence for there is little variation between our graduate and undergraduate student preferences (Figure 1). There was a trend that the graduate students were more active and the undergraduates more reflective, but the difference in the median ranking was not statistically significant (Table 4).

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Table 4. *Comparison of median learning styles of undergraduate and graduate students in BME at The University of Texas at Austin.*

Level	N	**Active (-) to Reflective (+) (Median +/- stdev.)**	**Sensing (-) to Intuitive (+) (Median +/- stdev.)**	**Visual (-) to Verbal (+) (Median +/- stdev.)**	**Sequential (-) to Global (+) (Median +/- stdev.)**
Undergraduate	110	1.0 +/- 4.3	-3.0 +/- 5.4	-5.0 +/- 4.3	-1.0 +/- 4.4
Grad	95	-1.0 +/- 4.7	-1.0 +/- 5.3	-5.0 +/- 4.6	-1.0 +/- 4.8
		P = 0.1257	P = 0.9451	P = 0.6523	P = 0.9772

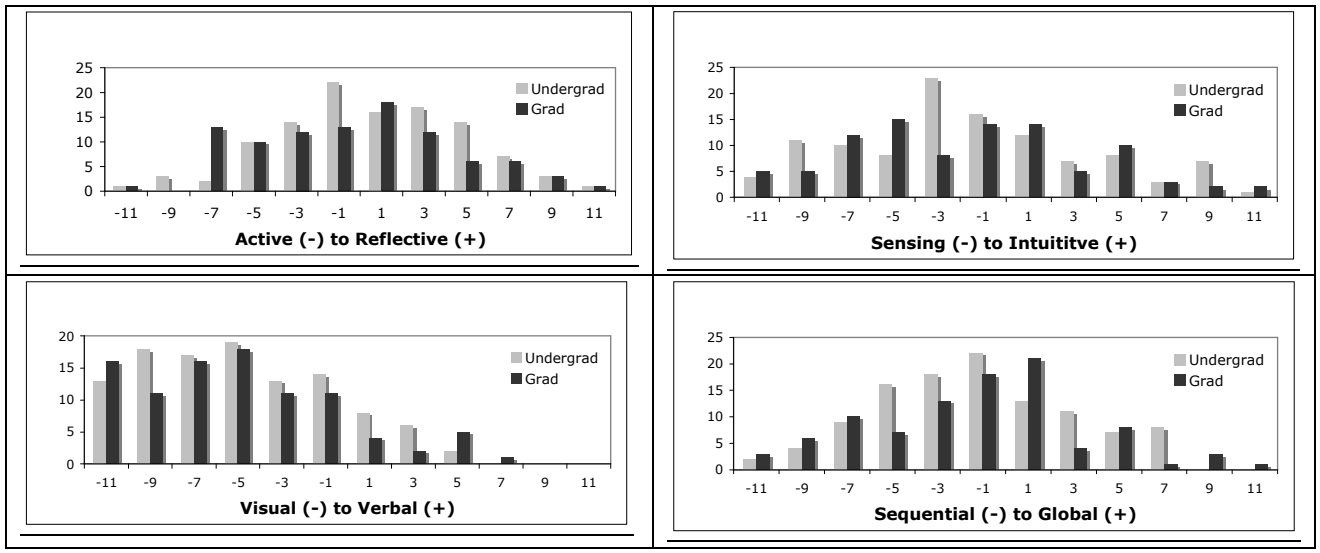

Figure 1. ***Learning style preferences for graduate and undergraduate BME students at The University of Texas at Austin.***

<u>3) Do students' learning styles impact their use of instructional technologies?</u>
Studies have looked at achievement and hypermedia-assisted instruction without finding any conclusive results. One extensive review on hypermedia as an educational technology postulates the current array of learning styles inventories may not be able to ascertain the nuances in a relationship between learning styles and achievement[13].

Within BlackBoard®, one can obtain counts of the number of times that different aspects of the system were accessed by the students. We used a Spearman rank correlation coefficient to quantify the relationship between each learning styles dimension and the number of BlackBoard® accesses. In particular, in BlackBoard® we evaluated the frequency with which students accessed the announcements section, discussion board, staff information section, and the tool for checking their grades ("my grades"). Data were pooled across all semesters, with the

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exception that BlackBoard® access data were not available for spring 2004 and spring 2005. We tested against the null hypothesis that the correlation coefficient was zero.

Different learning style preferences did correlate with different BlackBoard® usage patterns (Table 5). Frequency of usage of the announcements feature was higher for students who preferred a more sensing style vs. a more intuitive style, whereas no correlation was seen between the number of accesses of the announcements and the other learning style dimensions. Preference for those with a reflective style was associated with more frequent access of the discussion board; no statistically significant correlations with the other learning styles dimensions were observed. None of the learning styles dimensions were correlated with the number of accesses of the staff information section. The majority of students used the staff information pages only a few times over the semester (Figure 2). A small number of students accessed the staff pages with high frequency, but we have not yet identified an underlying commonality among those students. In our analysis, preference for those with a sensing style was correlated with utilization of the BlackBoard® tool for checking ones' grades; no statistically significant correlations with the other learning styles dimensions were observed.

Table 5. Correlation between learning style dimensions and BlackBoard® usage statistics.

	Active Reflective	Sensing Intuitive	Visual Verbal	Sequential Global
Announcements	-0.03 (p = 0.74)	*-0.19 (p = 0.02)*	-0.01 (p = 0.89)	-0.09 (p = 0.24)
Discussion Board	*0.16 (p = 0.04)*	-0.10 (p = 0.21)	-0.07 (p = 0.35)	-0.03 (p = 0.70)
Staff Information	-0.07 (p = 0.37)	-0.02 (p = 0.77)	-0.09 (p = 0.24)	0.09 (p = 0.27)
My Grades	-0.02 (p = 0.84)	*-0.18 (p = 0.02)*	-0.02 (p = 0.78)	-0.04 (p = 0.66)

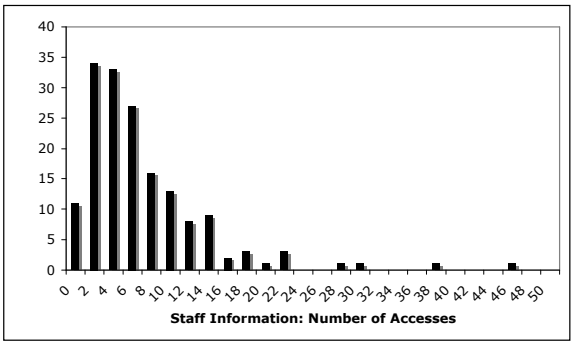

Figure 2. Frequency with which students access the staff information of the course Website.

In addition to BlackBoard® usage data, we analyzed student survey data regarding issues associated instructional technologies such as frequency of use, comfort in use, communication with instructors, communication with peers, knowledge of course deadlines and requirements, review of course materials outside of class, on-going feedback about progress in the course, problem-solving practice, and understanding of "real-world" value of course material.

Our previous findings[3] indicate that students were more comfortable with MATLAB® at the end of the semester than at the beginning. They gave a higher rating for the value of MATLAB® when it comes to practicing problem-solving skills. Students also highly rated MATLAB® for helping them to see real-world applications. We re-analyzed the data separately for the four

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learning styles (a preliminary version of this analysis was presented at ASEE Gulf-Southwest 2007). Based on a Wilcoxon Signed Rank test, the same trends in student comfort with MATLAB® were seen for different learning styles groups. With regard to the value of MATLAB® for problem solving practice, some of the increases were no longer statistically significant when the data were stratified by learning styles. However, that could be simply due to the decreased sample size. Some additional study of this matter for students with active and sensing styles may be warranted. Similarly, some of the increases in recognition of the real-world value of the materials were no longer statistically significant when the data were stratified by learning styles, presumably due to the decrease in sample size.

In 2006, students were asked to rate the extent to which they agreed with statements about computer programming, learning, and intelligence. These statements were: You have a certain amount of basic intelligence and you can't really do much to change it, You can learn new things, but you can't really change your basic intelligence, You have a certain amount of aptitude for computer programming, and you can't really do much to change it, You can learn new things, but you can't really change your basic aptitude for programming, The faster you learn, the more intelligent you are, and It's not fair to expect you to learn on your own or from other students. We found high correlations between the two items about intelligence (0.74) and between the two items about programming (0.84). There was a low to negligible correlations among other combinations, with the strongest (up to 0.3) being between attitudes about intelligence and programming items. We assessed the correlations between ratings on each LSI dimension and agreement with the six statements. We found most of the correlations were small. The highest correlation was between SEN/INT dimension and the first statement about programming skills. The more strongly a student scores as a "sensor", the more s/he believes that her/his programming aptitude cannot be changed.

We did not uncover any clear evidence that students with different learning styles derive different benefits from using MATLAB® in our course. Some results, however, suggest that learning styles may correlate with beliefs that can hamper learning of computer programming.

4 Conclusions and Future Work

Our first question addressed whether or not our BME students' learning styles reflect those of other engineering student populations. According to Felder's research, engineering students tend to be active, sensing, visual, and sequential. Given that our study population is strictly BME students, we thought there might be a possibility for differences. Anecdotally, we hear that many of our BME students would not have selected an engineering major at all had BME not been available; instead, most would have opted for a major in the natural sciences. We found that our BME students were more reflective than has typically been reported for engineering students. Consistent with reports for other engineering student populations, our students are strongly visual. Thus, professors should make a concerted effort to use more pictures, graphs, diagrams, flow charts, and demonstrations. Keep in mind that we all learn more when information is presented both verbally and visually. Good instruction involves multiple strategies and we have found that the instructional technologies are useful in addressing student learning style preferences.

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Our second question on graduate vs. undergraduate student learning style preferences indicated there isn't a big dichotomy between these students. In contrast, some research suggests that faculty and student learning styles are often different and graduate students look more like faculty populations. In our study, we did not disaggregate the master's level and doctoral level students. It is possible that some variations between master's and doctoral students could impact this analysis.

Our final question looked at whether learning styles impact student use of instructional technologies. Within a tool like BlackBoard®, students have the flexibility to find an approach that meets their preferences. For example, reflective students like the discussion board and an activity such as writing short summaries is a useful approach. Announcements are well received by sensors. Currently BlackBoard® includes a feature that sends out an email when an announcement is posted. Students have the option to subscribe or not to subscribe to these notices. Our study was done before this was an option. Professors can share critical information in multiple formats (i.e., the discussion board, announcements, emails).

The issue of student beliefs with regards to programming, professors should keep in mind that sensor students might be more concerned about their ability to program. Provide these students with hands-on, concrete examples in small steps so that they can experience success. It also may be important to direct them to the syntax so that they feel they have been given adequate guidance.

Our future work will study possible correlations with demographics like gender, race, and ethnicity. It should also be noted that no corrections for multiple comparisons were performed in this analysis.

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Biographies

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