Identifying Student Profiles Related to Success in Discrete Math CS Courses

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1 Introduction

The growing demand for Computer Science graduates has led to growing enrollment in Intro to CS courses. Unfortunately not all students who enter these courses succeed [9]. Researchers in Computer Science education are working to identify sets of student features that play a role in course performance and that could directly lead to the design of interventions that could improve student outcomes [4]. Specifically, researchers studied whether motivation is related to course outcomes and retention [7], whether high performing students have different study behaviors than low performing students [4], and whether other sources such as sense of belonging and stress contributes to the struggles that students face [6]. This prior work mainly focused on introduction to programming courses. In this paper we focus on another important gateway course in the computing sequence: Discrete Math. This course involves conceptual problem solving that requires students to think about a problem and conceptually understand it before starting to work on it. This might require different study behaviors than those needed when working to compile code where trial and error might help forge a way towards a solution. The theoretical mathematical nature of the course might also alter students motivation.

2 Methods

Our goal was to discover student profiles that might be associated with performance in a Discrete Math course. We surveyed students in two different offerings of the course Fall 2021 and Spring 2022 and checked to see which features correlated with final grades in these courses. We surveyed students early in the semester to get information about them as they enter the course. We reasoned that if these features correlate with success then the findings can lead to the design of an intervention for future students.

2.1 Participants

During Fall 2021, we surveyed 69 students from the Discrete Math course in the introductory computer science sequence at the University of Illinois Urbana Champaign. The total number of students in the course was 477. During Spring 2022 in a different offering of the same course, we surveyed 347 students. The total number of students in the class was 829. Only students who answered an IRB approved questionnaire were included in the study. The consent and questionnaire was sent out via Qualtrics. Students in Spring 2022 received extra credit for completing the questionnaire. This partially explains the difference in response rate between semesters.

2.2 Data Collection

Students were asked to volunteer and answer a questionnaire with 60 questions that were taken from the following validated instruments: the Index of Learning Styles [8], the Intrinsic Motivation Inventory [1], the Growth Mindset Scale [2], and sense of belonging questionnaire [5].

2.3 Instruments

The Intrinsic Motivation Inventory is an instrument that assesses participants' intrinsic motivation based on the following six subscale scores related to performing an activity: Interest/Enjoyment, Perceived Competence, Effort/Importance, Pressure/Tension, Perceived Choice, and Value/Usefulness. It is designed based on self-determination theory [1]. Students respond on a 5 point Likert scale of "Strongly agree" to "Strongly Disagree" to the following 2 questions from each subscale. "I think this class is going to be boring" and "I think this class is going to be enjoyable", "I think that I am going to be pretty good at this class" and "This is a class that I cannot do very well in", "I plan to put a lot of effort into this class" and "It is important to me to do well in this class", "I am anxious about this class" and "I feel very relaxed about this class", "I feel like it is not my own choice to do this class" and "I feel like I am taking this class because I have to", "I believe this class could be of some value to me" and "I believe doing this class is important".

The Index of Learning Styles [8] is a survey instrument used to assess preferences on four dimensions (active/reflective, sensing/intuitive, visual/verbal, and sequential/global). The instrument was developed and validated by [8]. Users answer 44 a-b questions with 11 questions for each of the four dimensions. After answering the question students get a score for each of the four dimensions that ranges from 0 to 11. for example, the 11 items that corresponded to the Activist/Reflective spectrum were added with a score of 1 if the response corresponded to Activist and a score of 0 if the response corresponded to Reflective.

Sense of belonging to one's college major is a feeling of membership and acceptance. Prior work identified it as important to student success [3]. One way to assess a sense of belonging is to ask students to report how they think others see them with respect to being savvy in their field [5]. Students respond on a 5 point Likert scale of "Strongly agree" to "Strongly Disagree" to the set of the following 4 questions: "my teachers see me as a computer scientist", "my friends/classmates see me as a computer scientist", "my family sees me as a computer scientist", "I see myself as a computer scientist".

Growth Mindset introduced by Dweck [2], is about students' beliefs of where intelligence comes from and how these beliefs influence behavior in the face of challenges. The Growth

Mindset Scale [2] assesses student's mindset by asking 3 questions on a Likert scale of 1 to 6 ("You can learn new things, but you can't really change your basic math ability.", "Your math ability is something that you can't change very much". "You have a certain amount of math ability, and you can't really do much to change it.").

3 Results and Discussion

We found positive correlations between calculated final grades and the average of the responses to the Intrinsic Motivation Inventory (IMI) questions ($p < .001$) for both Semester 1 and Semester 2. Students with higher grades agreed more with statements from the IMI such as "I think that I am going to be pretty good at this class", "It is important to me to do well in this class". A Wilcoxon rank-sum test with the Low and High groups significantly differed with the High students scoring higher on the motivation responses ($p < .05$)

The Index of Learning Styles assesses preferences on four dimensions: Active/Reflective, Sensing/Intuitive, Visual/Verbal, and Sequential/Global. We looked for correlations between final grades and student's scores for each of the dimensions. We found a negative correlations between the Activist/Reflector dimension and calculated final grades for both Semester 1 ($p < .05$) and Semester 2 ($p < .001$). Students with higher grades ranked lower on the dimension which means that they are more likely to be Reflectors than Activists. For example, when asked to respond to an item such as "When I am learning something new, it helps me to" the students with higher grades were more likely to choose "Think about it" rather than "Talk about it".

In future work, we plan to examine how we might turn this information into an intervention. We plan to share with students how they compare to other students in the class. This might draw student's attention to the idea that in this class thinking about the solution before attempting to solve it is a good learning strategy. They might revise their study strategy accordingly.

Belonging. We found a positive correlations between student responses to their sense of belonging and calculated final grades ($p < .05$) for Semester 1 but not Semester 2. In Semester 1, students with higher grades agreed more with statements such as "I see my self as a computer scientist" and "my family/friends see me as a computer scientist". A Wilcoxon rank-sum test with the Low and High groups significantly differed during this semester with the High students scoring higher on Belonging ($p < .05$). In future work we will explore whether this difference is due to the different student populations. A large but different proportion of non CS students take the class in both semesters. In semester 1 27% of the students are CS majors. In Semester 2 55% of the students are CS majors.

Growth Mindset We found no correlations between student responses to the growth mindset questions and their final grades ($p > .1$). In future work we plan to explore whether there is a correlation with responses to Growth Mindset not with final grades but with the improvement in grades from midterm to final grade.

3.1 Student Profiles

In previous sections we reported that students who were high performers were rated higher on intrinsic motivation. We also found that high performers were rated higher as reflectors. We wanted to know how many of these students are both motivated and reflectors. Is it the case that students who are motivated don't need to be reflectors, or that students who are reflectors don't need to be motivated to succeed? As Figure 1 and Figure 2 show, we found that many of the students who were high performers were both. Each figure depicts the entire data set of students for one of the semesters. As the figures show, most of the high performers are either motivated, reflectors, or both. In comparison, very few of the low performers are both reflectors and motivated.

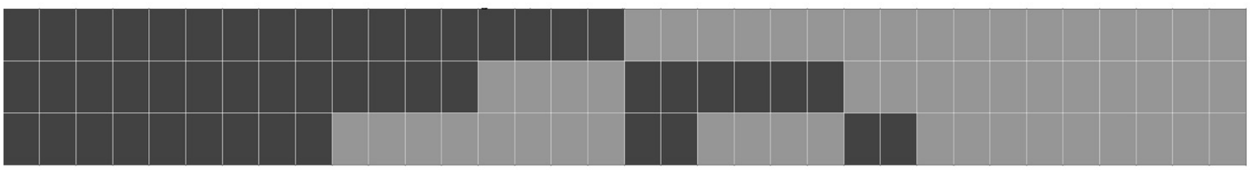

Figure 1: Semester 1. Each column represents a student. Black squares in the top row are High performers and white are Low. Black squares in the middle row have have high motivation. Black squares in the bottom row are Reflectors and white are Activist

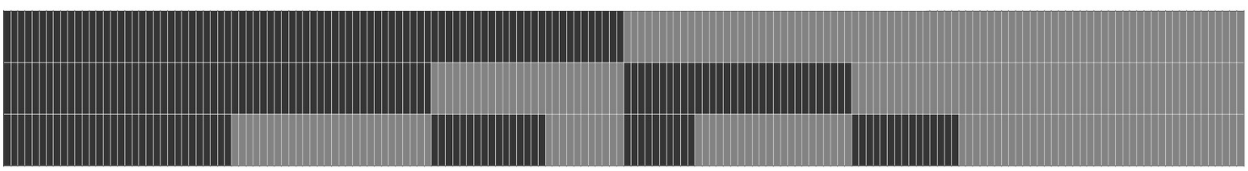

Figure 2: Semester 2. Each column represents a student. Black squares in the top row are High performers and white are Low. Black squares in the middle row have high motivation. Black squares in the bottom row are Reflectors and white are Activist

4 Conclusions

In this paper we examined student profiles that might be associated with performance in a Discrete Math course with the underlying goal of designing an intervention that will help students improve their course performance. We found a correlations between final grades and student motivation. Students with higher grades agreed more with statements such as "I think that I am going to be pretty good at this class".

We also found a correlations between the Activist/Reflector Learning Style dimension and final grades. Students with higher grades ranked lower on the dimension which means that they are more likely to respond as Reflectors rather than Activists. For example, when asked to respond to an items such as "When I am learning something new, it helps me to" the students with higher grades were more likely to choose "Think about it" rather than "Talk about it".

In future work, we plan to examine how we might turn this information into an intervention. We plan to share with students how they compare to the average of responses in the class. As a result students might attend extra study sessions early in the course.

Our approach can be helpful to educators. It is straightforward to survey students using the instruments we collected during the first week of class. Student responses can inform the educator about the student population, their motivation, sense of belonging, mindset and learning styles. An educator can then provide advice to students about the specific factors that correlate with success in this particular course.

Further, qualitative data has been collected but not analyzed that may help to explain these findings related to how students actually prepared for exams and studied for the course. We found no significant correlation between sense of belonging and final grades. In future work we plan to explore different ways of getting at sense of belonging questions beyond the ones we used here.

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