Measuring Self-Regulated Learning: A Tool for Understanding Disengagement in Calculus I

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Calculus 1 has been and continues to be a key gateway course to STEM majors, which contributes to a loss of students in the STEM pipeline. Student-learning behaviors impact performance and, in turn, the student experience. By analyzing early online homework activity and help seeking, rich descriptions of students can be used for early prediction for at-risk students, but can be misrepresentative for students who have not yet engaged with these resources. This preliminary report presents self-regulated learning (SRL) theory as a way to understand student behaviors. Using this framework, online tools were designed to collect behavioral data which was used to create a SRL score based on in-course student activity. This preliminary report presents findings on the relationship between student behaviors in Calculus I, a behavioral SRL score, and failure rates, particularly with students disengaged with course content.

Keywords: Calculus I, Self-Regulated Learning, Learning Behaviors

Calculus I is commonly identified as a weed-out course for students majoring in STEM disciplines. This is further supported by data gathered from the Mathematical Association of America national calculus study that reports a 25% DFW rate nationally at research institutions. Additionally, they report that Calculus I students experience lowers confidence in, enjoyment of, and the desire to continue pursuing a degree requiring mathematics (Bressoud & Rasmussen, 2015). Research evidence suggests that how students engage with their studies effects success (Vandamme, Meskens, Superby, 2007). By leveraging the high level of data that can be collected from online engagement and digital interactions, we theorize that it may be possible to identify students early in the semester, based on their behaviors with digital content, who are at-risk of being unsuccessful (defined as a grade of D or F here) in Calculus I (Fonti, 2015; Hu, Lo, & Shih, 2014; Macfadyen & Dawson, 2010). In the past, techniques from learning analytics and data mining have been employed with relative success using early performance data to predict course outcomes. In this study we use data from the Canvas LMS (quiz-log data), the online homework system, and sign-in logs from when students visit the calculus help center (CHC).

While fine-grained interactions with digital resources can provide a rich set of data about individual students, those who do not engage with resources can be easily be misrepresented by their digital footprint, as their temporary disengagement can result for many reasons. Self-regulated learning (SRL) theory provides a way to better understand student behaviors.

This preliminary report presents initial findings toward understanding disengaged students' self-regulation, academic performance, and learning behaviors. We draw on student interactions with online tools developed around SRL theory and then organized into a behavioral SRL score. We aim to address the following research questions:

1. *Can we quantify SRL through student interactions with online tools?*
2. *How does SRL relate to academic performance, particularly for those students that are disengaged in the course content early on?*

Theoretical Framework: Self-Regulated Learning

Mathematics students often cannot identify mistakes in their work, why the mistakes exist, or how to change their study habits to address their mistakes (Zimmerman, Moylan, Hudesman, White, & Flugman, 2011). SRL - "the self-directed process by which learners transform their mental abilities into academic skills" (Zimmerman, 2002, p. 65) - enables students to develop an understanding of their learning processes so that they can implement strategies and modify their study habits and learning behaviors to address difficulties to become more successful learners. Zimmerman's (2000, 2002) three-phase process model provides the SRL framework for this proposal. The phases focus around a learning task and consist of a planning phase (forethought), performance phase, and self-reflection phase – each occurring before, during, and after the learning task, respectively. The model is cyclic, with each phase informing the next. The cyclic nature of SRL allows students to continually review course material and deepen their understanding of concepts, which can promote learning, transferability, and retention (Bannert, Sonnenberg, Mengelkamp, & Pieger, 2015; Sonnenberg & Bannert, 2015).

Forethought

The forethought phase consists of task analysis and self-motivational beliefs around the learning task. Task analysis involves setting goals and identifying strategies to employ so that those goals can be achieved (Zimmerman, 2000, 2002). Self-motivational beliefs involve "self-efficacy beliefs, outcome expectations, task interest or value, and goal orientation" (Zimmerman, 2008, p. 178). A student's beliefs regarding their self-efficacy about a task impact the value placed on that task and, in turn, the motivation and expectations of how effort for task will be executed. When a strategy cannot be identified, confidence and motivation play a role in determining if the learner intends to seek help. The forethought process connects directly to beliefs about one's learning (Zimmerman, 2002), influencing how the performance phase will be carried out.

Performance

The performance phase is where strategies identified in the forethought phase are implemented. Elements of regulation of performance require self-control and self-observation, where one can modify or adapt the strategies identified during forethought to optimize the learning process. Self-control competencies such as time management and attention focusing are key during this phase to be able to make such adjustments (Zimmerman, 2000, 2002). By monitoring and having a record (mental or physical) of event details and duration during the performance phase, one can assess current and future adjustments that may need to occur. Upon completing the task (i.e. finishing the performance phase), learners reflect on their processes.

Self-Reflection

Self-reflection involves learners looking back on their performance to assess what went well and where improvements could be made. This phase involves judging performance and then reacting to that judgment. Self-judgment means evaluating one's own performance to some personal standard, and self-reactions will differ depending on whether or not that standard was met (Zimmerman, 2000, 2002). For example, a student may receive a C on an exam, when, in fact, they had anticipated an A. The student may then react by changing study habits or strategies. Results from the self-reflection phase then impact subsequent forethought and performance phases of future tasks in this cyclical process as students move forward.

Measuring Self-Regulated Learning

The most commonly used instrument for measuring SRL is the Motivated Strategies for Learning Questionnaire (MSLQ) - an 81-item self-report questionnaire that assesses “college students’ motivational orientations and their use of different learning strategies for a college course” as well as their “goals and value beliefs” (Pintrich, Smith, Garcia, & McKeachie, 1991, p. 3). The MSLQ has primarily been used to study components of SRL and the relationship of the components to academic performance (Pardo, Han, & Ellis, 2016; Pintrich & De Groot, 1990; Pintrich, Smith, Garcia, & McKeachie, 1993; Zimmerman & Kitsantas, 2014). However, due to the nature of self-reports, student responses on the MSLQ tend to reflect “how they [think] they should study, rather than how they [do] study” (Worthley, Gloeckner, and Kennedy, 2015, p. 137). Further, the validity of the MSLQ has been put into question, as it does not always align with observable behaviors such as strategy usage (Winne & Jamieson-Noel, 2002). While the three-phase cyclic model of SRL describes the learning process, methods to find evidence of SRL outside of self-reports are non-trivial (Winne & Baker, 2013). To address this discrepancy, we designed online tools specifically to coax SRL into observable, measurable events that can be recorded, which led to the formulation of a behavioral SRL metric.

Methods

For this research, online tools were developed and implemented through the university’s learning management system (LMS). They were based on the three SRL phases: forethought, performance, and self-reflection. Since students often struggle with precalculus content (Agustin & Agustin, 2009), we focused on SRL around the task of assessing and remediating one’s knowledge of precalculus topics at the start of the semester. A self-assessment (forethought), content quiz (performance), and post-quiz reflection (self-reflection) were created, all of which were optional for the students.

Focusing on the forethought phase, we designed a Prerequisite Self-Assessment (SA), an 8-item survey asking students to rate their confidence in correctly answering questions on relevant prerequisite material on a Likert Scale from one (No confidence) to five (Very Confident). By assessing their confidence in precalculus topics, the tool determines if students were engaging in the task analysis component of forethought – how well they think they know the material.

Students’ participation in performance phase of SRL was determined by whether or not the student took the Prerequisites Content Quiz (CQ). The CQ is comprised of 12 multiple-choice and multiple-answer questions about prerequisite material essential for Calculus I. Upon finishing the CQ, students received information on what questions they answered right and wrong. When any question was answered incorrectly, immediate feedback was provided, including the relevant topic to review and available resources. Student responses, time spent per question, and order in which questions were answered can provide insight to better understanding the performance phase of SRL, as these data provide information on self-control and strategy implementation.

Students were given a five-item survey called the prerequisite reflection tool (RT) which was intended to be used after the CQ. The RT asked students questions such as ‘What topics from the prerequisite content quiz do you plan to study?’ and ‘How do you plan to study/practice problems from the prerequisite content quiz material?’. Use of the RT provides evidence that a student is reflecting on his or her performance on the CQ. This behavior indicates that a student may be planning to address possible content weaknesses, but does not provide evidence of subsequent follow through (i.e. additional forethought and performance of the intended task) without further investigation, such as tracking access of resource materials.

Formulating a Behavioral SRL Metric

Of students that used the SA, they were considered to have either high confidence (mean confidence score of three or greater) or low confidence (mean confidence score less than three). Students that completed the CQ were considered to have either high precalculus ability (score of eight or greater) or low ability (score less than eight). Results from the SA and CQ were combined with use of the RT (used or did not) as well as precalculus resource access (accessed or did not) to formulate a behavioral SRL score. Results in each of these categories produced 36 different possible outcomes, and each outcome was then evaluated using Zimmerman's three-phase model as to whether or not they needed to remediate and if they were self-regulating appropriately. Each behavior was then assigned behavioral SRL scores of 0, 20, 40, 60, 80, or 100, from 0 (no self-regulation) to 100 (highly self-regulating).

Data and Initial Findings

In addition to data gathered to compute the behavioral SRL score for each student, course performance data, online homework access data, and CHC attendance was collected. Online homework for the entire course was due at the end of the semester. Success in Calculus I was identified by a final letter grade of A, B, or C. Grades of D and F were classified as failure.

Table 1 presents the distribution of behavioral SRL scores across the 376 consenting students with the failure rate for each group. The same data is also shown for students that were considered 'disengaged' in the course with regard to both digital interactions with online homework and in person help-seeking in Calculus I as of week four. For example, 64 students had an SRL score of 60, 31.2% of which failed the course. In addition, 23 of these students were identified as being disengaged with the course, and 52.2% of these disengaged students failed.

Table 1: Statistics for Behavioral SRL Score Within Two Groups: All Students and All Disengaged Students.

Behavioral SRL Score	Number of Students	Failure Rate	Number of Disengaged Students	Failure Rate
0	32	46.9%	20	60%
20	50	32%	16	56.2%
40	18	27.8%	6	16.7%
60	64	31.2%	23	52.2%
80	104	24%	29	31%
100	108	17%	23	21.7%
Total	376	26.3%	117	41%

Within both groups, failure rates tend to decrease as students' behavioral SRL score increase, with the exception of the small group of students who have a behavioral SRL score of 40. Additionally, the subset of disengaged students has a particularly high rate of failure.

To begin validating the behavioral SRL score, we compared mean behavioral SRL scores with students' behavior with online homework and help seeking in the CHC. Of these four groups, the disengaged students, those who had neither been to the CHC nor worked on their Calculus I course online homework as of week four, had the lowest mean behavioral SRL score (56.1), while students who both sought help and used the online homework had the highest mean score (72). Those who only worked on online homework had slightly higher mean behavioral SRL score (70.3) than those who only sought help (mean score=63.2). A Kruskal-Wallis nonparametric test verified that these four behavioral groups differ in mean rank behavioral SRL score, $\chi^2(3)=15.0625$, $p=0.013$. Post Hoc Dunn's test with FDR correction revealed that the mean rank of disengaged students are statistically lower than students who only engage in the calculus course online homework before Exam 1, $z=-3.67$, $p=0.0018$, $r=0.21$.

Discussion

These preliminary findings show promise for being able to use an SRL framework to develop tools that measure students' SRL behaviors and identify which disengaged students are potentially at-risk of failing Calculus I. Using these tools, we developed a method for generating SRL scores for students by analyzing their behaviors, specifically those around prerequisite remediation and readiness for Calculus I. The relationship between SRL scores and academic performance metrics suggests that more self-regulatory behaviors around prerequisite material promote success in course performance, which aligns with what is seen in the literature (Labuhn, Zimmerman, & Hasselhorn , 2010; Zimmerman et al., 2011; Zimmerman & Schunk, 2001). These statistical relationships grow stronger when looking at only those students who are disengaged with Calculus I before their first exam. Students who are disengaged, but have a higher SRL score tend to have higher success rates in the course than those who are disengaged with lower SRL scores. Similarly, when looking across all students (not just those who are disengaged), we see that students who have higher SRL scores generally fail less on average, showing the benefit of measuring SRL for all students.

Limitations and Future Direction

In this report, presence of the different phases of SRL was determined by whether or not the students used the designed online SRL tools. This method relies on students' understanding the purpose for each tool and makes the assumption that lack of use is a conscious effort to avoid the tool and the associated SRL phase. We recognize that this has limitations as we have yet to further develop ways to measure SRL for students that do not use online tools. In moving forward, while we recognize there are several limitations, we plan to address the following two: (1) student awareness of online tools and their purpose, and (2) student usage of a selection of tools rather than engaging with all tools, which leads to a lack of evidence of students' SRL behaviors (e.g. despite a student reflecting on CQ performance, they fail to use the RT). As part of our efforts in addressing these limitations, we plan to merge multiple tools into one.

Student self-regulatory behaviors around prerequisites leave breadcrumbs about their self-regulation in Calculus I. This may help frame the temporary disengagement of some students as intentional regulated prolonging of engagement. For instance, a student well positioned in Calculus I may temporarily divert their exam study time to a different class in which they are struggling. Preliminary reports show some success with using high and low behavioral SRL scores as predictors for success and failure in Calculus I. Further, when focusing on disengaged students, our methods for identifying those at-risk of failure become more precise. Based on student interactions with online tools and other external resources, we are deepening our understanding of SRL's role in Calculus I with student learning behaviors. While this data combined with the SRL framework is informing modification, enhancements, and addition of online tools, we plan to conduct student interviews as a way of triangulating our data. We plan to use Zimmerman and Pons' (1986) protocol as another way to measure SRL. Student interviews will provide an opportunity to better understand student engagement in the course as well as validate our quantitative findings. SRL scores and qualitative data can then inform intervention support to improve student success in Calculus I and STEM.

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