Modeling Temporal Self-Regulatory Processing in a Higher Education Biology Course

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1. Introduction

Science education in the 21st century must not only provide students with content knowledge, but also the skills and dispositions necessary to be literate consumers and producers of scientific knowledge claims (FNBE, 2014; NRC, 2012; Rocard et al., 2007). These modern education goals require revisioning science instruction from traditional lecture and transmission models of teaching to active learning pedagogies focused upon students' engagement in science practices where teachers can surface, support, and evaluate students' ongoing conceptual understanding (Dirks, 2011; Haak, HilleRisLambers, Pitre, & Freeman, 2011; Kober, 2015; PCAST, 2012). There is growing evidence that such active pedagogies can propel students' learning and ameliorate achievement gaps (e.g., Eddy & Hogan, 2014; Freeman et al., 2014), but students' likelihood of capitalizing upon these pedagogies depends upon their ability to self-regulate their learning (Greene, 2018; Sinatra & Taasoobshirazi, 2018). Self-regulated learning (SRL; Zimmerman, 2013) occurs when students actively pursue academic goals, and when necessary, effortfully enact planning, monitoring, controlling, or evaluating processes to maintain or adapt various aspects of learning (i.e., cognition, metacognition, motivation, affect, context). Such processing is not innate, but it can be acquired (Bjork, Dunlosky, & Kornell, 2013), and students who can enact SRL effectively and efficiently are more likely to benefit from active learning pedagogies in science education, and to achieve academic success, than their peers who struggle to self-regulate (Dent & Koenka, 2016; Eilam & Reiter, 2014; Richardson, Abraham, & Bond, 2012; Schraw, Crippen, & Hartley, 2006).

Modern SRL research has revealed the kinds of processing associated with success in science (Chen et al., 2017; Dent & Koenka, 2016), but more work is needed to understand when, how, and why students self-regulate or fail to do so (Ben-Eliyahu & Bernacki, 2015). Effective self-regulation is inherently temporal (i.e., dynamic over the various phases of learning; Zimmerman, 2013) and adaptive (i.e., responsive to moment-to-moment changes in context and performance). Investigating and understanding such SRL processing requires (a) multimodal, multi-channel log data regarding how students interface with content over time (Azevedo, Taub, & Mudrick, 2018), (b) methodologies capable of modeling these interactions, as well as (c) contexts in which such SRL processing has tangible effects upon academic performance (Bernacki, 2018). In this study, we utilized multimodal log data from a college-level, active learning pedagogy biology course spanning in-class (e.g., responses logged via live quizzing devices) and out-of-class (e.g., activity in the learning management system [LMS]) events alongside assessment data to understand how adaptive enactment of SRL processing over time could predict student performance. A better understanding of how students do and do not enact SRL as they move from early to later stages in a particular course, in response to changing internal and external conditions, is necessary for the development of the next generation of interventions for promoting effective self-regulation and learning in science (Johnson, Azevedo, & D'Mello, 2011; Schunk & Greene, 2018; Winne, 2001).

1.2 Post-Secondary Science Education

Despite common acknowledgment of the need for an increase in the number of science, technology, engineering, and mathematics (STEM) graduates, post-secondary coursework remains predominantly didactic, and insufficiently engaging for many students (Hurtado, Eagen, & Chang, 2010; Maton, Pollard, McDougall Weise, & Hrabowski, 2012; PCAST, 2012). Active learning pedagogies have advantages over other more traditional pedagogies by emphasizing student engagement during and outside of class via activities such as group work, formative assessments allowing instructors to surface and respond to students' understanding, and inquiry as opposed to passive listening (Dirks, 2011; Freeman et al., 2014; Kober, 2015). Numerous researchers have found that, compared to traditional pedagogy, an active learning pedagogy is associated with an increase in performance for all STEM students (Crimmins & Midkiff, 2017; Freeman et al., 2014; Scott, Green, & Etheridge, 2016), as well as attenuation of achievement gaps found with underrepresented minority and first-generation college students (FGCS; Eddy & Hogan, 2014).

Compared to traditional courses, many active learning courses also require students to engage in more and different kinds of learning activities, including online readings, inquiry, and formative assessments that provide students with opportunities for learning and feedback outside of the classroom (Scott et al., 2016). Further, in active learning courses students are responsible for enacting appropriate processing in through early, middle, and late phases of the course as well as adapting their processing across these phases accordingly. These activities are positively correlated with exam grades (Lieu, Wong, Asefirad, & Shaffer, 2017). Given their unfortunate rarity in higher education, the mere presence of active learning pedagogies and tools (e.g., formative assessments, online resources) does not guarantee students will know how to benefit from them. There is a clear need for more research on student thinking and action during active learning in STEM, including why students do and do not take advantage of active learning affordances and how such activities relate to performance (Devolder, van Braak, & Tondeur, 2012; Eilam & Reiter, 2014; Sinatra & Taasoobshirazi, 2018; Zohar & Barzilai, 2013).

1.2 Self-Regulated Learning

Across multiple frameworks (e.g., Pintrich, 2000; Winne & Hadwin, 2008; Zimmerman, 2013), SRL is generally understood to involve a loosely sequential, temporal, goal-directed, adaptive process in which learners, when presented with a learning task, define its features, set a goal and a plan for achieving it, and then engage in learning by enacting strategies. Learners' motivation guides their initiation and sustainment in this process, and they supervise their own learning through an ongoing metacognitive monitoring process in which they consider the efficacy of their learning strategies for bringing them closer to their learning goal. If they are making progress, they sustain their efforts. If not, they adapt their tactics, or consider adjusting their goal to one that can be met. Effective SRL processing early in the course (e.g., defining tasks, planning) may differ from SRL later in the course (e.g., reviewing material, self-testing, monitoring efficacy and efficiency). Research has shown that these SRL processes are predictive of academic performance and learning across a wide-variety of contexts (Dent & Koenka, 2016; Devolder et al., 2012; Richardson et al., 2012; Zohar & Barzilai, 2013).

Modern models include the assumption that SRL is not a fixed attribute but rather a set of learnable knowledge, skills, and dispositions (Winne & Perry, 2000). Evidence of learners' SRL knowledge, skills, and dispositions can be inferred from discrete, observable events such as when a student highlights text or takes a practice test. Such observable events can serve as traces of cognitive and metacognitive processing. Researchers have made inferences about SRL processing via other methods as well, such as concurrent self-report of mental processes (i.e., think-aloud protocols, Greene, Deekens, Copeland, & Yu, 2018), and unobtrusive forms of ambient data collection such as log-files of students' interactions with LMSs (Bernacki, 2018). Observations of SRL processing, such as those used to generate trace data, allow researchers to assess what learners do over time, and how they might alter their processing contingent upon the efficacy and efficiency of their performance (e.g., Binbasaran Tüysüzoğlu & Greene, 2015). Compared to retrospective self-report methods, the real-time collection of these various kinds of trace data, either via direct observation of student behavior, or think-aloud protocol or log-file data, provides greater confidence in the measurement of SRL knowledge, skills, and dispositions, and allows for more sophisticated analysis of their temporal and adaptive nature (Ben-Eliyahu & Bernacki, 2015; Bernacki, 2018; Winne, 2001; Winne & Jamieson-Noel, 2003; Zhou & Winne, 2012).

1.3 Temporal and Adaptive SRL with Trace Data

SRL processes are cyclical, temporal, and adaptive in the way they unfold in light of current goals, prior events, and learners' metacognitive monitoring of them (Bernacki, 2018). Thus, it is critical that such processes are observed at a precise level of detail so that these adaptations can be captured in sequence. LMS trace data afford this fine-grained level of analysis by recording each event distinctly within a larger log. For instance, if a student in a biology class clicks to access a study guide in preparation for an upcoming exam, the server logs the student's identification number in the system and the timing of the request with a date, hour, minute, and second. The name of this study guide (e.g. "Unit 1 study guide") is recorded in another column. This log can be inspected to make inferences about SRL processing (e.g., students accessing practice test results are engaging in metacognitive monitoring), which can be used to test theoretical assumptions about SRL including its temporal nature (e.g., SRL enactment early in a course predicts performance later in the course; Zimmerman, 2013) as well as how learners adapt their processing contingent upon their performance (e.g., if particular strategies lead to academic success then they should be continued, if not, then they should be changed; Bernacki, 2018).

These raw data can be further enriched by creating aggregate events that all typify similar activities into less granular classes. Such aggregation can be helpful when it matters less what specific example of SRL processing learners enact than whether or how often they are enacting a type of SRL processing. For example, prior to an exam sometimes students access the syllabus and other times they access the course calendar. If the specific accessed resource matters less than the fact that the student is thoughtfully preparing for the exam, then researchers can classify both events as reflecting "planning" and measure the number of times each student engages in that category of activity (Bernacki, 2018; Vosicka & Bernacki, 2017). Similar aggregation can occur for instances of monitoring (e.g., judgment of learning, feeling of knowing) and strategy use (e.g., elaboration, inferencing). Such LMS aggregated event data can be used to examine the frequency of their occurrence within various critical periods in the course (e.g., the total number of planning, strategy-use, or help seeking events during the first few weeks of the course, versus similar data collected during a subsequent unit). Given research showing that students' early SRL processing can predict later performance (Bernacki et al., 2016, 2017), it is important to study how to understand such processing, and how to help students enact it more effectively.

Early research using log-file data primarily involved laboratory settings where researchers traced navigation and annotation behaviors (e.g., Hadwin, Nesbit, Jamieson-Noel, Code & Winne, 2007). Traces of classroom learning can also come from LMSs and intelligent tutoring systems that log students' problem-solving performance and help-seeking behaviors (e.g., Azevedo et al., 2013; Bernacki, Aleven & Nokes-Malach, 2015). Our study makes a unique contribution to this growing literature because (1) the LMS was used in an educational context and thus may capture more authentic learning behaviors than tasks assigned in the lab, and (2) the measurement period spanned multiple units in the course, long periods of time, and concurrent face-to-face as well as online learning opportunities. Further, (3) materials were designed and posted by university instructors rather than researchers. Our data allow an investigation of temporal assumptions of SRL (i.e., SRL processing early in the course should predict subsequent performance on course assessments) as well as the adaptive nature of SRL (i.e., changes in SRL processing should be informed by current and predicted future performance).

1.4 Purpose of this Study

We conducted this study to gain a better understanding of how LMS trace data can be used to capture the temporal and adaptive nature of SRL and how those aspects of SRL processing predict later course performance. Using aggregated multimodal trace and performance data from the first two units of an introductory college biology course, we investigated the following research questions:

RQ1: Do students systematically differ in the frequency of their enactment of SRL processing early in the course?

RQ2: Do these systematic differences predict course performance?

RQ3: Do students adapt the frequency of their enactment of SRL processes over time?

We used the first research question to determine whether there were relevant differences in student SRL worth investigating. Research question 2 addressed the temporal nature of SRL, specifically whether early SRL processing predicted later performance. Research question 3 provided insight into whether adaptivity was associated with learning. Specifically, adaptivity would be supported by evidence of differences in SRL enactment across units in the biology course and whether those differences were associated with learning.

2. Method

2.1 Participants

We examined data from a Fall 2015 Principles of Biology course (i.e., BIOL101) with 440 registered students, but the population of our analysis was limited to the 408 students who registered for the course prior to the first day of class and ultimately completed the course and received a final letter grade. Of the 408 students, 67.16% were Female, 16.67% were members of an underrepresented minority group, 26.23% were a FGCS, 75% were first-year students, and 20.10% listed biology as a primary or secondary academic major. Seven percent of students did not achieve the minimum course grade of 70 percent or better that was necessary for advancement in many of the university's academic programs.

2.2 Procedures

BIOL101 was a large introductory, one-semester active learning course intended for both biology and non-biology majors. In addition to teaching biology concepts and competencies, the instructor designed the course to foster students' learning skills. The class utilized a hybrid delivery model. Guided by the ICAP (i.e., interactive, constructive, active, and passive) framework, during class meetings students were periodically asked to work in pairs or small groups on active learning tasks posed by the instructor (Chi & Wylie, 2014). Outside of class, students were required to complete online preparatory homework assignments that provided immediate feedback, hints, and tutorials, as well as timed quizzes. There were four multiple choice exams, three unit exams and a cumulative final, all completed in-class.

Students utilized four online systems to engage with course materials, as well as to communicate with peers and the professor. The university's online LMS, Sakai (Sakai Project, 2018), functioned as the students' primary access to course materials. Via Sakai, students gained access to static course materials such as the course syllabus, active reading questions, and lecture notes, as well as links to the other systems and resource sites utilized throughout the course. Students seeking help used Sakai to contact the course instructor, make office hours appointments, download documents provided for regularly scheduled supplemental instruction sessions, and visit the websites of both the university's learning and writing centers. Students were also encouraged to seek and provide peer-to-peer support via the class's online discussion forum, called Piazza (Piazza Technologies, 2018). In addition to Sakai and Piazza, Pearson publishing's (2018) dynamic learning platform, Mastering Biology, was used to deliver online, outside of class bi-weekly reading assessments, homework, and seven timed quizzes over the semester. Pearson's classroom response system, Learning Catalytics, was used to gauge student learning and participation during each class session. Thus, the LMS had numerous features that students could use to monitor and control their learning, but it did not directly teach or prompt SRL processing.

2.3 Data Sources

All the data for this study were derived from online sources. We used three of the four sources of multimodal student trace data in our analyses: Sakai interaction logs, Mastering Biology assignment item interactions, and Learning Catalytics session results. The Sakai traces were generated each time students performed actions such as downloading documents, clicking links to external websites, or scheduling office hours within the LMS. Students' interactions with Mastering Biology were acquired via a standard instructor's report available within the learning platform. Finally, an instructor's report containing a student identifier, assignment titles, and scores was pulled from Learning Catalytics for determining students' class attendance.

2.4 Data Preparation

The primary goal of our data preparation was to create a single, uniformly formatted event log from our three sources of student trace data. The creation of a unified event log not only allowed us to more easily calculate the frequency of student actions on the various web-based systems utilized within the course, it also allowed for the analysis of SRL assumptions regarding temporality (i.e., SRL processing early in the course should predict subsequent assessment performance; RQ2) and adaptivity (i.e., changes in SRL processing across Units should predict subsequent assessment performance, RQ3). The unified event log contained at least four primary descriptive fields for each event: student identifier, timestamp, event code, and data source.

Creating the unified event log started with the processing of interaction data pulled from Sakai, which was already formatted to contain the desired four primary fields, but there were a large variety of event codes at arguably different levels of descriptive granularity. Event codes such as “syllabus.read “and “gradebook.studentview” were easily interpreted because they referenced predefined content areas within the LMS, whereas other event codes such as “content.read” and "webcontent.read" were much more ambiguous. To resolve this issue of ambiguity, the URL field of those events was used to determine the specific resource referenced by the event and a more detailed event code was provided for the event in our unified event log. Event entries for office hours appointments were also created from the Sakai trace data, based upon signup and cancelation activity, with the time of signup as the event timestamp. Additional attendance related events were generated by parsing the grades reported within Pearson's LearningCatalytics. Although technically not trace data, a student's class attendance on a specific lecture day was gleaned from the presence of non-null grade entry in the LearningCatalytics course administrator’s grade report for that day's assignment (see Table 1 for a list of all activity data).

From this fine-grained log of student activity data, we created larger categories indicative of common processes in SRL. For example, information acquisition is a foundational aspect of learning, and there are many ways students could engage in this activity. As shown in Table 1, students could acquire information by attending class, accessing readings, accessing exams from previous semester, or a number of other activities. Differences in these fine-grained activities are likely idiosyncratic; one student may have extensive biology background and only need to access prior exams to learn necessary information, whereas another student with less background may need to do more of the basic reading. Each student would be enacting effective SRL processing based upon their own idiosyncratic information acquisition needs, therefore differences in these fine-grained activities are likely not informative. Instead, it is more helpful to aggregate all of the activity data categorized as information acquisition and look at differences in student enactment within this larger category. Such aggregation mirrors work Greene and Azevedo (2009) conducted with think-aloud protocol trace data, and they found that the aggregated categories were better predictors of student learning than the finer-grained activity data. Table 1 shows how we categorized each activity coded from the server log, and the larger categories we subjected to data analysis. As two other examples, Metacognitive Help Seeking was comprised of two actions performed to schedule a help session, which we interpreted as the result of prior enacted metacognitive or calibration skill, such as realizing that one's standards were not being met, and some kind of adaptation was needed (Winne, 2001). Our General Metacognition category was based on a similar assumption that accessing the gradebook or item analyses on past exam performance were reflective of metacognitive monitoring of performance.

2.5 Latent Profile Analysis

We used latent profile analysis (LPA) to investigate whether there were unobserved groupings (i.e., profiles) of students who systematically differed in their pretest scores and LMS activity across Units 1 and 2. Then, we examined whether these profiles of students, on average, systematically differed on exam 2 through 4 scores, as well as on their final course grade. Given the large number of coded activities and their likely idiosyncratic nature, we used the smaller number of aggregated categories as indicator variables in our LPA (Dominguez, Uesbeck, & Bernacki, 2016). A series of confirmatory LPA models were estimated using Mplus 8. Data-model fit criteria included lower information criteria values, as well as statistically non-significant Lo-Mendell-Rubin adjusted and bootstrapped likelihood ratio tests. Models with higher entropy values were also considered better fitting.

3. Results

3.1 Descriptive Statistics

On average, exam scores rose over the course of the semester, culminating with a fairly high final grade in the course (see Table 2). However, there were relatively large standard deviations for each exam, as well, implying variance that we attempted to model using LPA. In terms of LMS activity in each Unit, there was a general decrease from Unit 1 to Unit 2, except in the case of information acquisition activity, which rose almost 700% from Unit 1 to Unit 2. Metacognitive activity remaining fairly consistent in frequency across Units, whereas course management activity dropped. The latter finding is not surprising given that course management activities are expected to be higher in the beginning of the course, as students become familiar with the syllabus and schedule, and download necessary materials. Exam and final grade scores were strongly correlated, but not to the degree that multicollinearity was a concern.

3.2 Latent Profile Analyses

Our first research question was: Do students systematically differ in the frequency of their enactment of SRL processing early in the course? A series of LPAs, each increasing the number of tested profiles, were conducted. The latent profile indicators for each analysis included pretest and Exam 1 scores, as well as cognitive and metacognitive category variables from both Unit 1 and Unit 2. We utilized Mplus's auxiliary function to include exams 2-4 scores and final course grade as outcome variables. As shown in Table 3, all information criteria, entropy, and likelihood-ratio tests showed improved data-model fit as the number of profiles were increased. However, the 4-profile analyses, despite replicating the best loglikelihood value, produced a model with a non-positive definite first-order derivative product matrix, indicative of a poor solution. The 3-profile analysis also replicated the best loglikelihood value but had no estimation errors. In addition, the sample sizes for the 3-profile analysis were 324, 14, and 70, respectively, whereas for the 4-profile analysis they were 313, 70, 19, and 6. Again, the very small sample sizes for the third and fourth profiles suggested this model was inferior to the three profile solution. An argument could be made for a 2-profile model being the best model, given the small sample size of one of the profiles in the 3-profile model. However, Table 3 shows that there were notable improvements in all indicators of data-model fit from the 2- to 3-profile model, thus we concluded that the 3-profile model was the optimal solution. Therefore, we were able to answer research question 1 in the affirmative: there were systematic differences in SRL processing worth investigating via research questions 2 and 3.

3.3 Predicting Course Performance

Our second research question addressed whether the systematic differences in early SRL processing found in research question 1 were predictive of course performance, and therefore supported one aspect of the assumption of temporality in SRL. Our LPA estimation included auxiliary prediction of the Exam score outcomes, similar to an ANOVA with profiles as the levels of the categorical independent variable. For each unit exam (i.e., exam 2, 3, and 4) as well as the final grade, the overall test of profile differences was statistically significant (all ps $< .05$), with Profile 3 outperforming Profile 1, which in turn outperformed Profile 2 (all ps $< .05$). This indicates that, on average, students in Profile 1 earned the highest score on each assessment, followed by Profile 3, with Profile 2 students earning the lowest scores (see Table 4). However, Profile 3 did not statistically significantly outperform Profile 1 on Exams 3 or 4 ($p > .05$). Given Profile 2's relatively low sample size, we erred on the side of caution and focused our analyses on Profiles 1 and 3. Hedge's g for Profile 1 versus Profile 3, for exams 2, 3, and 4, and for final grade were .304, .210, .061, and .307 respectively. These are small to medium effect sizes. Therefore, we found support for our second research question: on average, the systematic differences in early SRL processing in the course predicted subsequent course assessment performance. In other words, we found support for the temporality assumption of SRL models.

The LPA results indicated overall differences in latent profile indicators across profiles. Descriptively, students' average pretest and Exam 1 scores did not differ greatly between Profiles 1 and 3 (see Table 5 and Figure 1). On the other hand, differences in the frequency of SRL processing across profiles were predictive of subsequent course assessment performance (see Table 5 and Figure 1). During the period comprising Unit 1, students in Profile 3 interacted much more often in the LMS than students in Profile 1, and the same was true for the period for Unit 2. This difference in overall activity was mirrored in two other indicators, where students in Profile 3, compared to those in Profile 1, more frequently engaged in course management and metacognitive activities. A slight difference in information acquisition behaviors, with Profile 3 students engaging in this more often than Profile 1, was present during the Unit 1 time period, but not in the Exam 2 time period. Thus, we found evidence of the temporality of SRL: the students in Profile 3 engaged in more frequent course management, information acquisition, and metacognitive activity early in the course compared to students in Profile 1, and these differences were associated with subsequent assessment performance, particularly for Exam 2 and final course grade. Our last research question was focused upon the nature of those systematic differences, and whether there was evidence of adaptivity in the data.

3.4 Adaptivity in the Frequency of SRL Enactment Over Time

Our last research question required an investigation of differences in SRL enactment across the first two units of the course. In both profile groups, the frequency of SRL enactment, as captured by our trace log, decreased from Unit 1 to Unit 2 except in the case of information acquisition, which showed a sharp increased from Unit 1 to Unit 2. This does suggest adaptivity, as students in both Profile groups decreased activities such as course management and help-seeking and increased their attempts to learn material. Metacognition remained relatively consistent across units, which is not surprising given the pivotal role it plays in SRL and student success (Winne, 2001). However, we did not find evidence of differences in adaptivity between Units 1 and 2 across Profiles. For the most part, students in each Profile decreased their overall activity. Profile differences persisted in terms of overall activity level, course management, and metacognition.

4. Discussion

In this study, we analyzed multimodal trace data from college students' online activity during a biology course to investigate whether early SRL activity predicted subsequent assessment performance (i.e., temporality) as well as whether students changed their SRL processing after the first exam (i.e., adaptivity). Utilizing aggregated trace data within a person-centered analysis approach, we found that when and how students engaged with active learning pedagogies predicted their subsequent exam performance. We found that more successful students engaged in more overall activity, specifically more course management and metacognition, their less successful peers. There was evidence of adaptivity between Unit 1 and

Unit 2, as on average students decreased their level of activity while also increasing their information acquisition behaviors, but there was no evidence that this adaptivity differed across groups or predicted assessment performance.

Our temporality findings align with theory and research on SRL regarding the importance of early task definition activities as well as the pervasive importance of metacognition throughout learning (Dent & Koenka, 2016; Winne, 2001; Zimmerman, 2018), providing additional evidence that students' facility at this type of higher-order thinking is a powerful tool in 21st century learning environments (Azevedo et al., 2018). Equally as important, our findings further demonstrated the viability of using trace data from online course resources (i.e., LMS data) to inform early warning systems that might identify students who may struggle in the course. In our data, patterns of activity predictive of poor performance were evident within the first and second exam period, which is early enough for educators to intervene and change students' performance trajectory (Dominguez, Bernacki, & Usebeck, 2016; Eddy & Hogan, 2014).

These findings support continued calls for finer-grained analyses of not only the kinds of SRL activities students enact, but also when and under what conditions (Schunk & Greene, 2018). SRL theory has focused upon the phases of learning, and optimal processing during those phases. Expansion of SRL theory will require understanding the conditions under which optimal adaptation are and are not made, as well as how the timing of those adaptations affects learning efficiency and efficacy. Overall, our findings provide support for continued theory development in SRL (i.e., expanding upon the temporal, adaptive, and contingent nature of SRL; Ben-Eliyahu & Bernacki, 2015) as well as the importance of course management and metacognitive activities early in the semester, including efforts to bolster such activities when it is still possible to deliver remediation interventions capable of changing students' performance trajectory (Dominguez et al., 2016).

4.1 Limitations

The fine-grained tracing of digital learning events and the analysis of their temporal and adaptive natures can further inform SRL theory and methodological advancements but are also not without limitations. These data were collected in a single context (i.e., one semester of biology coursework at a single university) and thus conclusions are constrained to that sample and course. Latent profiles are sample dependent and are a product of the context and individuals observed; solutions are likely to differ when those contexts and individuals differ. Results are further influenced by instructional design choices in terms of resources provided (i.e., LMS and e-texts) and learning objectives addressed and assessed on exams. Further, it is critical to acknowledge this was a face-to-face lecture course. Much of learning activity (i.e., all events involving printed or downloaded materials and those during face-to-face interactions in lecture sessions) went unobserved with this trace method.

From a theoretical perspective, further validation studies must be conducted to confirm our inferences about students' resources use, so that we can confidently discuss the SRL events described in these analyses (Vosicka & Bernacki, 2017). These threats to validity extend to events where students clearly engage with digital content, but the concurrent mental processes that unfold are not directly observed. A final threat to validity is the nature of data-driven analyses such as LPA. In each set of analyses, we applied a theoretical lens to determine which variables were appropriate to include in initial feature sets for models. Data-driven methods are an efficient method for handling the immense scope of data on digital learning produced by traced methods. It is imperative that researchers maintain a theoretical lens in developing targeted models and in their appraisal, validation, and reporting.

4.2 Future Directions for Research and Practice

Based on our findings, a key area for future research and practice involves developing and testing supports for learners' SRL in science learning both inside and outside of the classroom by (a) building prompts in the curriculum to encourage behaviors predictive of better course performance and (b) collaborating with campus partners to reinforce active learning strategies. These initiatives could be studied using randomized-control trials, with conditions hidden to students and instructors by using the LMS as the delivery mechanism.

Instructors of STEM courses could be encouraged to use frequent prompts, via classroom instruction or the LMS, to promote more frequent and spaced online activity. In the classroom, instructors, teaching assistants, and recitation leaders could repeatedly prompt students to download lecture notes, monitor grades, and schedule an appointment with the instructor. Within the LMS, automatic alerts could be created for students to self-test or download materials in a timely manner. Similarly, an alert could be created to prompt students who do not check grades within hours of a new grade posting.

Collaborations with campus partners can be built to intentionally support active learning pedagogies. For example, advisors and other instructional support staff could stress the importance of accessing course notes, reviewing outlines, and taking practice exams. We also recommend partnering with campus support services such as undergraduate learning centers to offer SRL instruction and tutoring across multiple subject areas and content-based services. The research literature shows that both automated and personalized, direct intervention are needed to help students enact appropriate temporal and contingent SRL to benefit from active learning pedagogies in science (Bernacki et al., 2016, 2017).

4.3 Conclusion

In this study, involving college students in an introductory, active learning STEM course, we demonstrated relations among SRL processing measured via LMS activity and academic performance in the course. Specifically, we found that students who engaged in more activity early in the course had higher assessment scores, on average, than their peers who engaged less frequently with the LMS. This demonstrated evidence of temporality in SRL: early activity did indeed predict subsequent performance. Likewise, we showed that students did adapt their SRL processing from the first to second unit, but that the most successful students maintained higher levels of overall activity, as well as higher levels of metacognition. Students seemed to redistribute their activity from the first to second Unit, focusing less on course management and more on information acquisition. Such changes illustrate the adaptive nature of SRL, and our findings suggest researchers should focus on analyses of SRL processing via multiple levels of aggregation and across multiple modalities. Practical implications of our findings include directions for intervention, including systems that promote thoughtful adaptation over time.

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Table 1

Trace Data Category, Activity, and Description

Category	Activity	Description
Pretest	Pretest	Baseline assessment of biology knowledge
Exam 1 Score	Exam 1	Student's Exam 1 grade on a scale from 0 to 100
General Activity	Presence	Online session count - login or logout of Sakai session
Course Management		
	Announcement	Read announcements in Sakai
	Messages	Interacted with message tool
	Calendar	Interacted with calendar
	Syllabus	Accessed course syllabus page
	Lecture Notes	Accessed lecture notes ppt
	Class Objectives	Accessed list of learning objectives per course unit
	Class Outlines	Accessed unit's class outline
	Discussion Board	Clicked link to Piazza discussion board
Cognitive Help Seeking		
	Homework Correct	Homework problem hint correct
	Homework Incorrect	Homework problem hint incorrect
Information Acquisition		
	Attendance	Attended class meeting or office hours appointment
	Current Exams	Reviewed current semester exam material
	Previous Exams	Reviewed previous semester exam materials
	Course Material	Clicked link to Mastering Biology
	Guided Reading Question	Accessed units' guided reading questions
	Additional Readings	Accessed additional readings
	Supplemental Instruction Resources	Reviewed materials provided by SI
	Homework Item	Viewed homework problem without submitting
	Homework Solution	Viewed solution to a homework problem
	Submitted Correct	Submitted a correct homework response

	Submitted Incorrect	Submitted an incorrect homework response
	Quiz Problem Correct	Submitted a correct quiz response
	Quiz Problem Incorrect	Submitted an incorrect quiz response
Metacognitive Help Seeking		
	Help Resources	Clicked link to writing or learning center information
	Signup	Interacted with office hours scheduler
General Metacognition		
	Gradebook	Accessed personal gradebook
	Item Analysis	Accessed exam item analysis for exam review

Table 2

Descriptive statistics and correlations of assessments and unit 1-2 activities

	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1) Pretest	52.88	14.56																	
Unit 1																			
2) activity	29.39	17.47	-.03																
3) course management	34.06	17.33	-.08	.60															
4) cognitive help-seeking	0.86	1.71	-.10	.28	.42														
5) information acquisition	3.47	1.48	-.10	.61	.34	.24													
6) metacognitive help-seeking	4.18	6.88	-.07	.08	.14	.13	.46												
7) metacognition	6.29	6.17	-.06	.54	.55	.36	.23	.02											
8) Exam 1 score	73.54	14.72	.30	.09	.05	-.02	-.01	-.02	.04										
Unit 2																			
9) activity	15.54	11.05	-.04	.77	.45	.23	.53	.06	.40	.11									
10) course management	13.03	10.62	-.09	.38	.53	.25	.23	.08	.32	.04	.54								
11) cognitive help-seeking	0.35	1.24	-.06	.04	.09	.23	.04	.01	.02	-.08	.16	.20							
12) information acquisition	20.42	3.83	-.11	.13	.00	.00	.22	.02	-.04	-.22	.08	.02	-.03						
13) metacognitive help-seeking	0.93	3.41	-.08	.10	.14	.18	.39	.72	.02	-.08	.09	.04	.05	.11					
14) metacognition	6.20	4.87	-.02	.50	.40	.27	.25	.14	.54	.14	.58	.34	.03	-.02	.12				
15) Exam 2 score	79.70	14.02	.22	.08	.01	.02	-.02	-.03	.02	.59	.15	.15	-.04	-.27	-.06	.09			
16) Exam 3 score	77.42	12.91	.25	.06	.02	-.06	-.03	-.04	-.03	.56	.12	.05	-.05	-.22	-.06	.06	.53		
17) Exam 4 score	77.60	11.79	.34	.02	-.01	-.04	-.10	-.05	-.03	.70	.07	.05	-.02	-.27	-.09	.03	.65	.68	
18) Final Grade	83.41	8.99	.30	.09	.05	.00	-.04	-.04	.04	.79	.16	.13	-.02	-.33	-.08	.11	.83	.76	.88

Note: Unit 1 or Unit 2 designation indicates that the indicator occurred during that particular time period.

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Table 3

Latent Profile Analysis Fit Indices

Number of Profiles	AIC	BIC	SABIC	LMR p-value	bLRT p-value	Entropy
2	39323.348	39495.832	39359.386	.142	<.001	.927
3	38728.219	38960.872	38776.829	.269	<.001	.952
4	38307.421	38600.244	38368.603	.419	<.001	.963

Note: AIC = Akaike Information Criteria; BIC = Bayesian Information Criteria; SABIC: sample-adjusted Bayesian Information Criteria; LMR = Lo-Mendell-Rubin adjusted likelihood ratio test; bLRT = bootstrapped Likelihood Ratio Test

Table 4

3-Profile Average Scores on Exams 2-4 and Final Grade

Profile	Sample Size	Exam 2 *M*(*SE*)	Exam 3 *M*(*SE*)	Exam 4 *M*(*SE*)	Final Grade *M*(*SE*)
1	324	79.048(.789)	77.189(.743)	77.720(.662)	83.085(.511)
2	14	75.712(2.115)	70.235(3.239)	70.376(2.297)	78.402(1.831)
3	70	83.470(1.883)	79.901(1.485)	78.484(1.551)	85.874(1.072)
Overall Chi-Square test values[a]		$\chi^2(2) = 7.803$	$\chi^2(2) = 7.750$	$\chi^2(2) = 10.119$	$\chi^2(2) = 12.984$

[a] All chi-square tests statistically significant $p < .05$

Table 5

Latent Profile Mean Estimates

Indicator	Profile 1 *M(SE)*	Profile 2 *M(SE)*	Profile 3 *M(SE)*
Pretest	53.511(.840)	44.649(2.418)	51.613(1.968)
Exam 1 score	73.445(.875)	63.604(3.956)	75.900(1.889)
Unit 1 activity	23.641(1.290)	37.115(5.609)	53.687(5.717)
Unit 1 course management	29.195(.850)	44.745(5.745)	53.845(6.799)
Unit 1 cognitive help-seeking	.521(.090)	1.925(.695)	2.164(.430)
Unit 1 information acquisition	3.067(.096)	6.591(.501)	4.651(.347)
Unit 1 metacognitive help-seeking	3.226(.254)	31.000(2.772)	3.245(.544)
Unit 1 metacognition	4.607(.359)	6.422(1.363)	13.848(2.284)
Unit 2 activity	11.857(.962)	23.043(2.786)	30.626(2.844)
Unit 2 course management	10.54(.577)	20.046(3.382)	22.853(3.202)
Unit 2 cognitive help-seeking	.279(.070)	.927(.448)	.547(.194)
Unit 2 information acquisition	20.221(.222)	22.211(1.037)	20.968(.617)
Unit 2 metacognitive help-seeking	.442(.069)	15.265(2.615)	.354(.139)
Unit 2 metacognition	4.773(.434)	9.771(2.103)	11.905(1.117)

Note: Unit 1 or Unit 2 designation indicates that the indicator occurred during that particular time period.

`

Figure 1

Latent Profile Means