Promoting Self-regulated Learning in Online Learning by Triggering Tailored Interventions

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ABSTRACT
In online education, students are expected to be independent learners who can self-regulate and reflect on their activities during the learning process. However, not all students have self-regulated learning (SRL) skills, and students with weak SRL skills tend to underperform in distance learning environments. The aim of our pilot study was to promote self-regulated learning in online education by triggering tailored SRL interventions automatically. As a first step toward, we constructed a quantitative research design where 58 students participated in 1) learning about introductory descriptive statistical concepts and 2) interacting with a self-paced online learning software throughout the experiment. We used the participants' action log files as a dataset to extract generalizable features, including pretest grade, quiz grade, reading time, and posttest grade. Then, we trained a random forest regressor model to predict student outcome (posttest). The correlation between actual and predicted posttest score was $r = .576$, indicating promise for accurately predicting and intervening. In the next phase of this work, we will apply SHAP (SHapley Additive exPlanations) to personalize SRL interventions by recommending each student to review the single topic that most negatively contributes to predicted posttest grade.

Keywords
Self-regulated learning, interventions, machine learning explanations, computer-based learning

1. INTRODUCTION
Students with different online learning skills, academic performance, and levels of technology experience may go through hardships to become autonomous learners who academically succeed in ever-growing online learning courses in universities. Previous studies demonstrated that successful academic achievement is strongly connected to the level of students' self regulative abilities, in which students take initiative in the learning process [8, 17, 14].

Self-regulated learning (SRL) skills are techniques for achieving academic success by regulating a student's own actions and decisions during the learning process [20]. Students with SRL skills are able to manage their own plans and reflect on learning progress throughout their learning.

However, distance learning poses threats to student success, especially students without SRL skills, since they are supposed to learn and complete assignments on their own. Having SRL skills in e-learning environments is particularly important for students to achieve academic goals, but SRL ability is not an inherent skill that every student possesses [9, 3]. Students lacking self-regulated skills are prone to underperform their peers who are able to direct their own learning process [22, 21]. Therefore, supporting students lacking SRL skills to develop into responsible and autonomous learners in online learning is crucial.

Our study responds to the need for SRL support by promoting self-regulated learning in an online learning environment via interventions automatically customized for each student. Many works demonstrated that aspects of student performance and experiences can be predicted by using students' action log files [15, 1, 16, 4, 6, 11, 5].

We take a step forward by using predicted student outcomes to trigger personalized SRL interventions in online courses. In our study, SRL interventions consist of suggesting that students engage in specific SRL behaviors, such as reviewing particular readings or quizzes that contribute to a lower predicted posttest grade. We emphasize triggering tailored interventions automatically for each student since it can help a particular student at the right time with interventions chosen by a machine learning model. The machine learning model in this case is designed to predict students' outcomes (specifically, posttest grade), while interventions are based on model explainability methods intended to discover SRL-related reasons why the model made a particular prediction.

Our study involves three conditions: the model training condition, the treatment condition, and the placebo condition. However, in this paper, we primarily discuss an investigation with the model training condition, in which we collect the data from students' action log files to train the machine learning model that will ultimately trigger SRL interventions in the treatment condition. We propose a method of 1) predicting student outcome (posttest grade) in online learning using machine learning techniques, and 2) triggering tailored SRL interventions for students by implementing SHAP (SHapley Additive exPlanations) analysis for the predicted student outcome. We focus on the methodological step #1 in this paper, but discuss ongoing work toward step #2. We evaluate aspects of this methodology in a study where students learned about introductory descriptive statistics concepts and interact with a self-paced online learning environment.

In our pilot study, we attempted to answer the following research questions:

- RQ1) How much do generalizable learning features (e.g., quiz/test grades) extracted from e-learning platforms predict student outcomes in machine learning models?
- RQ2) Is it possible to suggest each student to review specific topics from the learning module by triggering SRL interventions at the right moment?

2. RELATED WORK

2.1 Self-regulated Learning (SRL)

Previous studies have demonstrated the importance of self-regulated learning (SRL) in academic contexts [23, 14]. Particularly, researchers have focused on associations between self-regulated learning and academic achievements. Xiao et al. [17], Yusuf [18], and Zimmerman [19] investigated the reasons why students with self-regulated skills tend to accomplish strong academic achievement in their studies. Among 14 different types of self-regulated learning strategies that Zimmerman and Pons [22] identified in their research on students' learning strategies, our study primarily focused on reviewing records, which indicates student-initiated endeavors to review tests, notes, or textbooks for preparing further testing. Zimmerman and Pons collected data about participants' SRL strategies by conducting a structured interview and demonstrated how students from a high achievement group used reviewing strategies more frequently than lower achievers. The significance of developing SRL skills for university students has been further shown by other previous analyses [12, 8]. In an online learning environment, the importance of self-monitoring skills only increases since students are responsible for their own learning.

2.2 Modeling SRL

In order to analyze and measure students' self-regulatory behaviors in distance learning, researchers have used students' action log files in various ways. For instance, Maldonado-mahauad et al. [7] implemented process mining technique to detect self-regulated learning strategies and identified clusters of learners in Massive Open Online Courses (MOOCs). In another example, Segedy et al. [15] applied coherence analysis to interpret and characterize learner's behaviors in open-ended computer-based learning environments to shed light on students' SRL. In addition, there is a large body of research indicating that predicting student performance using event log files in e-learning is feasible [12, 2]. These studies concentrated on demonstrating detecting and characterizing students' SRL behaviors in online learning.

2.3 Intervening to Support SRL

Our study's primary objective is to apply SHAP analysis to extend current modeling methods so that they can support SRL in online education. In this regard, Mu et al. [10] took a very similar approach where they aimed to support wheel-spinning students in computerized educational systems by suggesting actionable interventions. This study is especially related to our study since they used SHAP to trigger individualized interventions. Our study differs in that we focus on SRL specifically, and will test the effectiveness of interventions experimentally, which is critical because the act of intervening based on a model's input features may then affect the model (e.g., perhaps reducing its accuracy).

3. METHOD

Our overall study design consists of an experiment with three conditions: the model training condition, the treatment condition, and the placebo condition. In this paper, we primarily focus on the model training condition where we collected data for machine learning model training and implemented SHAP analysis. The other two conditions (treatment condition and placebo condition) are currently collecting data with interventions from the model described here. Participants in the experimental condition group will receive tailored SRL interventions based on machine learning predictions, whereas students assigned to the placebo group will get SRL interventions almost identical to the ones from the experimental condition group except not based on machine learning predictions. In all conditions, including the model training condition we study in this paper, participants engaged in learning about introductory statistical concepts by using custom web-based online learning software (Figure 1). Figure 2 below illustrates an overview of our research procedure.

At the start of the study session, students completed a brief survey regarding their demographics and prior academic history. Following the survey, participants took a 10-minute pretest and used the self-guided learning session for up to 1 hour. The self-paced online learning environment included 12 different illustrated statistical readings, and one quiz to go with each reading (see partial screenshot in Figure 1). Throughout the learning session, students were not required to complete all the modules, and were allowed to complete the components more than once if they wanted to. After 30 minutes elapsed during learning session, each student received a simple baseline SRL intervention in which they were told which topics they had not yet viewed, or a list of topics in order from least- to most-viewed if they had viewed them all. Hence, in the model training condition, the intervention was not based on machine learning. The message prompt and the corresponding list of topics would, in theory, help to make aware patterns in the student's learning behavior up to that point in time, which could lead to reflecting more deeply about their current learning trajectory. Based on this information, we expected the student would be able to make more informed decisions on how to regu-

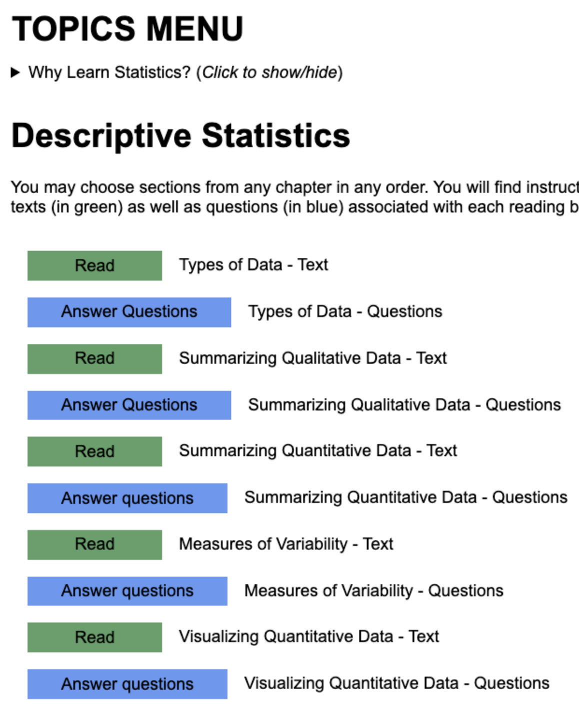

Figure 1: A portion of the topics menu from a self-paced learning session.

late their learning by adapting their future learning behaviors. This would allow for more systematic and controllable decision-making processes to determine which topics to visit or review, and make salient what areas they may feel to have not sufficiently studied. This intervention repeated every 10 minutes thereafter until the 1-hour learning session was over or the student chose to end it before the hour. Subsequently, they completed a 10-minute posttest with questions modeled after the pretest questions (but not identical).

3.1 Data Collection

We collected data from 58 university students who participated in our pilot study. Students were required to have completed either zero or one college-level statistics course, but not more, to avoid inappropriately matching introductory material to expert students. Students' event log files were extracted from the online learning system, which recorded their learning activities in real-time including information needed to provide interventions. These log files contained activities that were recorded during the students' interactions with every stage of the web-based online learning software.

3.2 Feature Extraction

Following data collection, we extracted each student's various features, including some attributes related to SRL behaviors, in order to use them as predictors for training the machine learning model. Students' interactions were distributed across various log files for each possible learning activity, quiz and test scores, time spent reading, and other files. For feature extraction, we merged all students' feature outputs into a single table which we later used for machine learning data analysis. Extracted features consisted of:

Prior to the self-guided learning session:

- Pretest grade (mean of multiple-choice question correctness)
- Time spent taking the pretest

During the self-guided learning session:

- Quiz grade for each 12 descriptive statistics quizzes
- Time spent reading each 12 descriptive statistics readings
- Number of times the student reviewed statistical readings/quizzes
- Number of events where the student clicked the button for going back to the Main Topics Menu
- Whether a student looked at other windows/tabs (i.e., the learning environment lost focus)
- Time spent completing the learning session

Following the self-guided learning session:

- Posttest grade
- Time taken for the posttest

Note that there were 12 versions of each quiz grade and reading time feature, each extracted from one of the readings or quizzes. Features following the learning session were outcomes, rather than predictors; in particular, we focus on posttest grade in this paper.

3.3 Data Analysis

From the extracted feature data, consisting of 58 instances (1 per student), we discovered some of the students did not seem to try their best to participate in our study. Five students did not attempt to take any of the quizzes from the learning session and their posttest scores were lower than their pretest scores. Nevertheless, we did not exclude these observations from our dataset since these students may reflect future treatment condition students and real-world classroom students.

We performed exploratory data analysis on the feature dataset and will discuss our findings in the Results (Section 4).

3.4 Model Training

Initially, we trained our model using a decision tree regressor to predict student performance (posttest score) using quiz grades, reading times, and pretest score (in Python using *Scikit-learn* [13]). However, the decision tree model did not yield stable R^2 values across 5-fold cross-validation. Since we had a relatively small dataset size for training a machine learning model, folds had, on average, 11–12 instances.

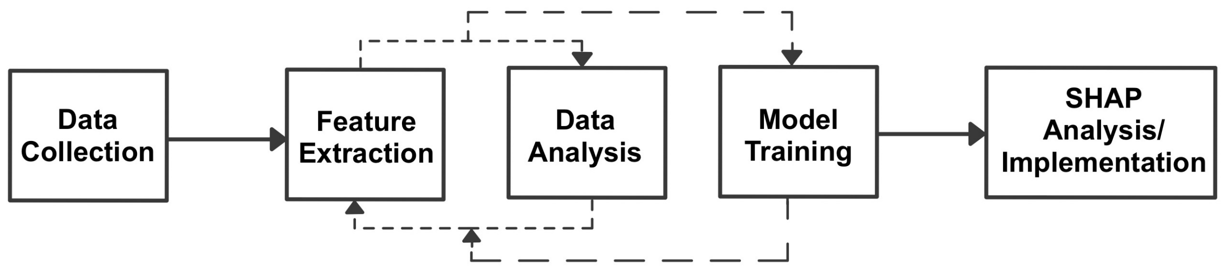

Figure 2: An overview of the research procedure.

Small folds contributed to instability in results since a decision tree might produce predictions for one fold with little or no variance. We thus changed to random forest regression, which can randomly sample observations and features to build a forest trees with ample variation between trees, which eliminated the problem of invalid R^2 values.

3.5 SHAP (SHapley Additive exPlanations)

Using posttest scores predicted by the Random Forest Regressor model, we implemented SHAP analysis to interpret the model prediction. We calculated SHAP values using the tree explainer to explain model predictions and will use these explanations (in the next steps of the project) to trigger individualized SRL interventions to meet each student's need. We sorted calculated SHAP values in ascending order to determine specific features that contribute to getting a lower posttest score.

4. RESULTS

In this section, we present findings on each stage of our research process in detail.

4.1 Data Analysis

We calculated Pearson correlations as a first step of data analysis in order to measure the strength of a linear relationship between posttest grade (target variable) and other potential predictor variables. We expected that clear relationships would be needed for the machine learning model to succeed given the small dataset size. Among the predictor variables, pretest grade had the highest correlation (r = .530), indicate at least one sizable—if unsurprising—relationship in the data. From this we discovered that students' initial knowledge (as evident from pretest score) was closely related to posttest grade.

However, quiz grade features and reading time features had promising positive correlation coefficients (up to r = .395). Though most features these were not statistically significantly related to posttest score given the large number of predictors and small dataset size, trends indicated that these were promising indicators for the success of machine learning methods. Since our goal was to suggest specific reading/quiz topic that students should review, we included 12 quiz grades and 12 reading time features for our predictors, along with pretest. Some features related to SRL had correlation coefficients trending in the expected direction, but in order to make our machine learning model simple, we did not use them as predictors. Moreover, we wanted to use highly generalizable feature types that could be easily extracted from diverse online learning platforms.

Within the chosen predictors, we checked whether pretest grade and posttest grade were normally distributed. We plotted frequency histograms for pretest grade and posttest grade features. Corresponding histograms were relatively bell-shaped and symmetric about the mean values, so we concluded that pretest and posttest grade features are normally distributed. This is essential to avoiding ceiling or floor effects for analysis of learning.

4.2 Extracted Features

Initially, we extracted 11 additional features from students' log files, but we used only pretest grade, quiz grade, and reading time as features for predicting posttest grade. Since we had a small sample size with 58 observations, we had to reduce the number of predictors to make the model simple. However, in future work with more participants we plan to use more predictors, such as features related to specific SRL constructs extracted via coherence analysis [15]. Moreover, we can include both SRL-related and unrelated features (e.g., pretest score in this study) and apply SHAP to disentangle the effects of SRL features, specifically, to provide interventions only on those.

In Figure 3, the left grey boxes represent the overall study process that students went through in our experiment. On the right, the figure shows the composition of a student's recorded action log file as a whole, which is composed of demographic survey, pretest, descriptive statistics surveys, reading times, log, browser tab focus, and posttest files. The diagram shows from which log files the predictors and a target variable were extracted.

Since students were not asked to complete all the reading/quiz components from the learning session, there were many participants who did skip several readings or quizzes. In these cases, we assigned -1 for corresponding reading times and quiz grade features to differentiate the cases. Table 1 below shows a statistics summary of extracted features, including minimum, maximum, and possible values that the features can take.

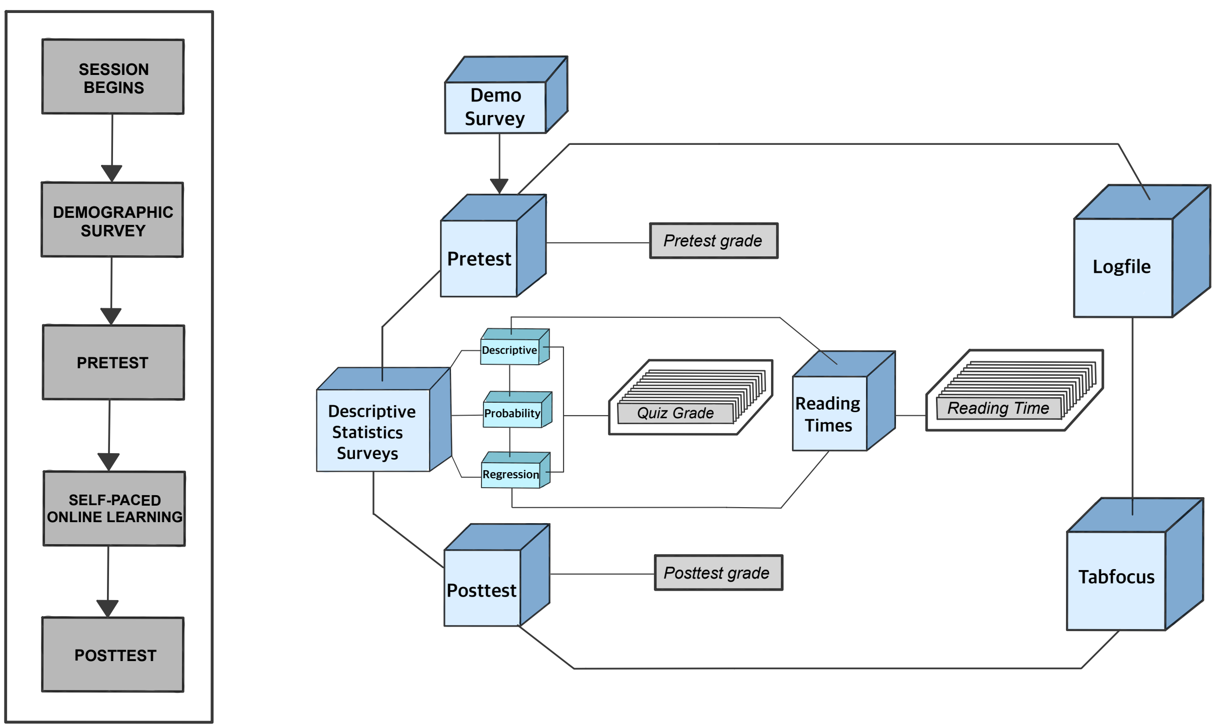

Figure 3: Overview of study stages (left) and data sources resulting from the study (right).

Table 1: Statistics of features. Note that it is possible for reading time to exceed the 60-minute session time if a student was not interacting (e.g., walked away from the computer).

	Pretest Grade	Posttest Grade	Quiz Grade	Reading Time
Min	8.3	25	-1	-1
Max	91.7	100	100	358 minutes
Possible Values	[0,100]	[-1,100]	[-1,100]	[-1,∞]

4.3 Machine Learning Model Training

We trained the random forest regressor model using pretest grade, quiz grade, and reading time features to predict posttest grade. We used 5-fold cross-validation for validation, as mentioned earlier, and measured R^2, root mean squared error (RMSE), and Pearson's r for model evaluation metrics. During the model training, we set the maximum depth of the trees to be 4 and fixed the random seed in order to produce a consistent outcome. We used 4 as a maximum depth of the tree because the results became notably more stable in initial tests (with a partially collected dataset) by reducing the depth of the trees.

After training, we evaluated the model and obtained the following results: 1) mean R^2 value within 5-fold cross-validation was .262, 2) mean RMSE was 15.17 (on a 0–100 posttest grade scale), and 3) mean Pearson's r was .576. From these observations, it is noticeable that our mean R^2 value was far from perfect averaged across folds. However, given the small data size we have, the trained model works relatively well. Furthermore, the accuracy was stable across folds: across the 5 folds, the standard deviation of R^2 was .067 and the standard deviation of RMSE was 2.20.

5. DISCUSSION

The objective of our pilot study was to promote self-regulated learning in online education by triggering individualized SRL interventions using machine learning techniques and SHAP values. To accomplish this, we began with extracting learning relevant features from 58 students' action log files which recorded students' learning traces during the online learning process. Using three types of predictors (pretest grade, quiz grade, and reading time), we trained a random forest regressor model to predict student outcome (posttest grade). Using the predicted student outcome, we applied SHAP technique to trigger personalized SRL interventions by recommending each student to review the single most learning session that contributes to getting a lower student outcome. As a result, we developed a flexible way of triggering individualized SRL interventions in a digital learning environment.

5.1 Significance

Our presented method is noteworthy in several aspects. Firstly, our proposed technique can be used as a means to help students who lack SRL skills, technology experience, or have weak academic performance to develop SRL skills in e-learning environments. Especially with the unexpected outbreak of the global COVID-19 pandemic, a large number of students are using online learning platforms as a way of learning and assessing learning outcomes. The need for methods to help students learn effectively online is thus increasing rapidly; we hope our proposed method can contribute to the technology development of helping students in online education.

Secondly, our approach is original in that we integrated complex machine learning techniques (i.e., a complex, non-linear regression model) with SHAP as a recent machine learning interpretability method to decide how to intervene. Previously, this idea had only been explored on archival data [10], and not for SRL interventions in particular.

5.2 Implications

The presented method can be useful in some respects. Students can receive personalized SRL interventions, which can help them to improve their outcomes and develop SRL skills in online learning. In particular, we can support specific groups of students who need the most help in online education. For instance, students with no prior experience using e-learning platforms tend to be less experienced with monitoring their learning activities. This group of students can benefit from the implementation of our method of triggering tailored SRL interventions since they would be exposed to suggestions that encourage them to engage in specific SRL activities.

Our method is highly flexible since we required only 58 students as a training sample (which is sufficient here, but could be expanded) and 3 types of predictors extracted from event log files for training the model and administering SRL interventions. In particular, the three predictor types are generalizable features (pretest grade, quiz grade, and reading time) which can be easily extracted from many online learning platforms. Moreover, most e-learning platforms store students' action in log files, so we expect that it is feasible to introduce our SRL intervention mechanism into online learning platforms. Thus, we expect this method to be applicable in a variety of computer-based learning contexts.

Our method will also allow researchers to explore the causal nature of educational interventions driven by machine learning models. For example, are students who spend more time on a specific topic doing well because of time spent on that topic (as implied by a causal interpretation of the model), or do students who do well also happen to spend time on that particular topic because of some unobserved trait? Our explorations of interventions based on the features will allow us to manipulate the inputs of models and explore the nature of these connections.

5.3 Limitations

Even though we had a fairly stable model accuracy within the sample size (N = 58), model accuracy might be improved substantially with more data. The current training data size limits the feasibility of extracting a large number of specialized features that might only apply to a small fraction of students. Moreover, there may be complex interactions between students' learning behaviors on different topics that require additional data to uncover. Likewise, if our model is applied into online courses where students take the course for no credit, then the expected effectiveness of our method might be weak since students may not be motivated to study in the same way that students taking actual courses for credit. Further data is needed to explore these effects.

Collecting additional data would also afford the opportunity to explore new types of features that could address some of the unexplained variance in our model. For example, there are many features unrelated to SRL, such as prior experience level, perceptions of statistics, and others that might improve model accuracy. We hope to address these gaps in the model in future work. Notably, the model explanation method used here will allow us to still provide interventions based on SRL features even with other features included.

Improved model accuracy might be most helpful when determining when to provide interventions and to whom, unlike our current approach in which every student receives an intervention at predetermined points in time.

6. CONCLUSION

Notwithstanding the aforementioned limitations, our pilot study made an effort to throw light on the matter of students struggling within online courses through integrating machine learning and SHAP to promote self-regulated learning in digital learning. In the near future, we hope students in the treatment condition produce better learning behaviors and academic outcomes when our proposed method is applied.

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