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Academic habits that drive student success - an XAI approach to action-state modeling

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Abstract

This paper presents the third-year results of the work supported by the National Science Foundation's Revolutionizing Engineering Departments (IUSE/PFE: RED) Program under the project titled "IUSE/PFE:RED: Breaking Boundaries: An Organized Revolution for the Professional Formation of Electrical Engineers." The study looks at action-state orientation and its impacts on student success. The first-year results were presented at the 2023 ASEE Conference in Baltimore, MD with the academic paper titled "Predicting Academic Performance for Pre/Post-Intervention on Action-State Orientation Surveys" (Uysal, 2023). The objective of the first phase of the study was to find out how survey responses could be used to predict whether a student could be considered at-risk for failing academically. The second-year results were presented at the 2024 ASEE Conference in Portland, OR with the academic paper titled "Tracking and Predicting Student Performance Across Different Semesters with Matched Action-State Orientation Surveys and Interventions" (Uysal, 2024). The objective of the second phase of the study was to analyze and quantify the effects of in-class interventions on student study habits and, ultimately, their academic performance using action-state orientation surveys as engineering students progress further in their respective curriculum. The paper's major findings included high accuracy models in predicting student performance from action-state surveys and a quantifiable change in their survey responses after the interventions to improve their study habits.

In this paper, we explore the differences between higher GPA (3.5 or higher) and lower GPA (3.49 or lower) students when it comes to their study habits using the Shapley method which was originally derived from cooperative game theory to fairly distribute the total gains (or costs) among participants based on their individual contributions. This method is now widely applied in machine learning interpretability to attribute the importance of each feature in a model's prediction, commonly referred to as explainable AI or XAI. The Shapley method will be applied to GPA predictive algorithms trained on both high and low GPA datasets to identify the features (in this case, the action-state survey responses to individual questions) that contribute the most to a student's academic outcome in a comparative framework to study

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the differences in the importance of study habits in contributing to their academic performance. Our hypothesis is that the feature rankings of high and low GPA students will be different to provide actionable information on which study habits should be stressed more for realizing higher academic potential in struggling students.

Introduction

Many factors contribute to the academic success of college students. While the importance of cognitive abilities is well-established (Richardson et al., 2012), the impact of cognitive control processes—specifically, how individuals sustain their efforts toward academic goals—and their role in shaping academically relevant behaviors remain less explored. This study focuses on analyzing the relationship between students' cognitive control, particularly their action-state orientation (Kuhl, 1992), and behaviors essential for academic success. In the third phase of the study, we examine the differences in study habits between students with higher GPAs (3.5 or above) and those with lower GPAs (3.49 or below) using the Shapley method, a technique originally derived from cooperative game theory to equitably allocate total gains or costs among participants based on their individual contributions. Using explainable AI methods, we study how the feature rankings (which correspond to survey responses) for high- and low-GPA students may differ, to gain actionable insights into which study habits should be emphasized to help struggling students achieve their academic potential.

Action-state model

Action-state orientation (Kuhl, 1922) explores how achieving goals is closely tied to self-regulating behaviors. This orientation emphasizes individual differences in managing actions needed for goal attainment. Action-oriented individuals excel at using cognitive control to maintain the effort required for progress, effectively setting, planning, and implementing academic goals. In contrast, state-oriented individuals may recognize similar goals and plans but struggle to sustain the cognitive control necessary to execute them due to i) hesitation which leads to difficulty starting tasks and procrastination, ii) preoccupation which leads to trouble resuming tasks after interruptions and iii) volatility which leads to difficulty maintaining focus and switching to more engaging and fun activities.

Recent work in the past decade has identified two key behaviors essential for academic success: i) extracurricular engagement involves participating in activities beyond the classroom and is linked to GPA (Bakoban & Aljarallah, 2015), degree completion (Flynn, 2014), and future earnings (Hu & Wolniak, 2013) and ii) study habits include strategies for managing academic work, such as finding quiet study environments and avoiding cramming, with research showing their positive impact on academic achievement (Nonis & Hudson, 2010). A common limitation in studies of these behaviors is the reliance on composite measures that aggregate diverse actions into single scores. These formative scales (Edwards & Bagozzi, 2000), mix incomparable behaviors, which limits their utility in providing actionable guidance. ***In this study, we will focus on analyzing individual behaviors through item-level analysis for more specific insights using an entirely data-driven approach which relies strictly on student survey data and self-reported GPAs.***

Data Collection

The papers presented in ASEE 2023 and 2024 focused on surveys conducted over approximately a two year span covering 5 academic semesters from 2021 to 2023 and a range of different courses and student cohorts which generally took the survey multiple times both prior to and after interventions in the classroom to improve study habits.

In this paper, we shift our focus to the latest 3 academic semester where a modified (shortened) version of the survey was conducted primarily for engineering students ranging from sophomore to senior in the Fall 2023, Spring 2024 and Fall 2024 semesters where a total of 783 responses were collected. The main objective behind the modified survey is to implement the sustainability aspect of the proposal to ensure data collection and analytics can continue beyond the project's end date in October 2025. In order to achieve this, the survey now includes a varying number of questions (anywhere from a minimum of 14 to a maximum of 24 including factual demographics questions for anonymous identification) for each student based on whether or not they have been subjected to a Canvas mini-course on improving study habits and whether or not they employed any of the strategies to improve their study habits.

The survey opens with the question in figure 1 below where baseline information is captured for each student in terms of their study habits and strategies. This is followed by a branching question where the student is asked whether they recall being given instruction (either in class or from a Canvas mini course) on strategies for staying focused and improving academic performance. If the answer is affirmative, a set of additional questions collect data first on the students' fundamental understanding of action-state orientation followed by another branching question to collect more data on which of the strategies covered in the mini-course they have implemented in their daily lives.

Think about the last 30 days of the semester. How often did you do each of the following?

	Never	Once/week or less	Most days	Every day
I studied in a place that had no distractions (e.g., noise, people talking).	○	○	○	○
I made sure no one disturbed me when I studied.	○	○	○	○
I responded to text messages or responded to social media while studying.	○	○	○	○
I studied in a quiet place.	○	○	○	○
I set study goals for the day.	○	○	○	○
I studied during the time I had planned.	○	○	○	○
I stayed up all night without sleeping to get schoolwork done.	○	○	○	○
I studied with a friend.	○	○	○	○
I did other activities (e.g., played a video game) while studying.	○	○	○	○

Figure 1: Survey opens with a question on study habits and strategies for each student

Data Preprocessing

The complete survey data includes 783 responses across Fall 2023, Spring 2024 and Fall 2024 semesters. Due to the branching nature of the survey, each individual submission may include a different number of responses which complicates how the data can be presented to a learning algorithm. The overall objective of the study is to use an explainable AI (XAI) method to first rank the features (which correspond to survey responses) for both high- and low-GPA students to gain actionable insights into which study habits should be emphasized to help struggling students achieve their full academic potential. To use XAI – a machine learning algorithm must be trained on the dataset where contributions of each feature to the outcome can be measured and ranked which requires a set dimensionality for the tensor used in training in terms of the number of input features and the output value. We formulate this as a regression problem where the input to the algorithm includes all non-demographics questions and the output is the self-reported GPA.

For majority of the dataset (~540 unique responses), the input vector is 24-dimensional where the first 23 entries indicate responses to individual questions in numerical form and the last entry is the self-reported GPA. This first group of students includes the ones who have answered affirmatively to the question asking whether they recall being given strategies for staying focused and improving academic performance. For the rest of the dataset (~240 unique responses) where the answer to that question is no, the remaining survey questions are skipped, and the input vector is only 14-dimensional where the first 13 entries indicate responses to individual questions in numerical form and the last entry is the self-reported GPA. Since we want to study the difference in feature rankings for both high and low GPA students empirically, a relatively large volume of data is needed which ultimately led us to use the former group of students who answered the branching question affirmatively. Among this group, a smaller subset of students (~80) has left a significant number of questions blank and thus were also taken out of the dataset.   Table 1 below provides the final characteristics of the dataset before and after pre-processing.

Number of unique submissions	*Submissions with no prior training*	*Submissions with action-state training*	*Submission with incomplete responses*	*Submissions used in training/testing*
783	244	539	79	460 (240 / 220)

Table 1: Complete dataset characteristics – the last column shows the number of responses ultimately used in the study with 240 3.5+ GPA responses and 220 3.49- GPA responses

The final distribution of GPA values after the preprocessing of the dataset can be found in figure 1 below. While the overall distribution is more Gaussian like (as expected), the cohort distribution is more uniform for GPA > 3.5 and tilted for GPA < 3.5.

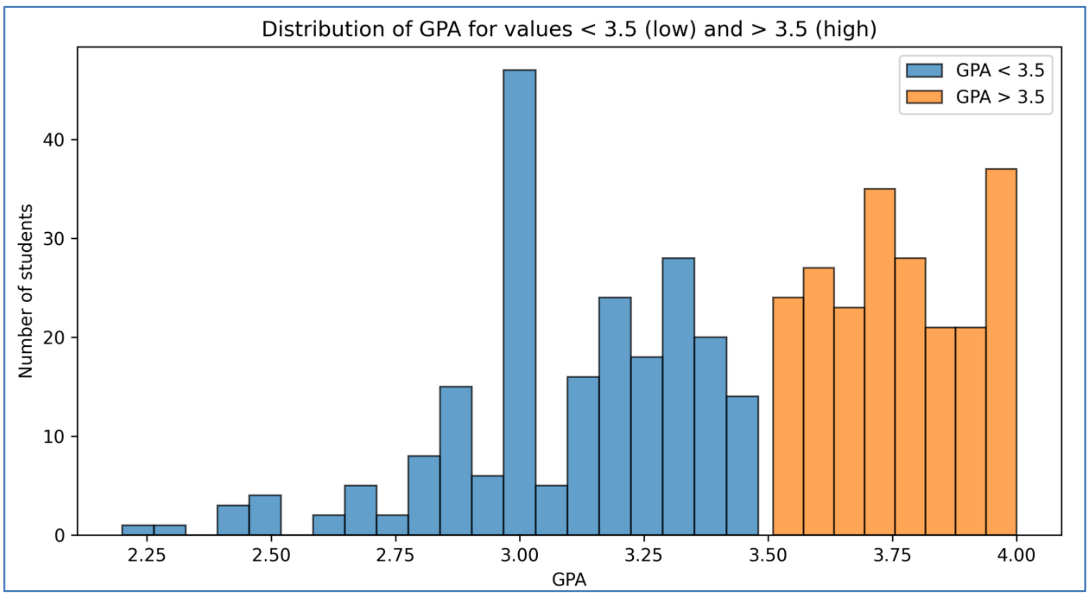

Figure 1. Color coded data distributions for the two cohorts (low and high GPA)

Methodology

In this study we used Random Forest regressor which yielded the best performance among a range of algorithms tested including linear regression and feedforward neural networks (Borup et al., 2023). A random forest is a versatile machine learning model widely used for both classification and regression tasks. It operates by combining the predictions of multiple decision trees, which are individual models that make predictions based on splitting data into smaller, more manageable subsets. Each tree in the forest is trained on a random sample of the data, and the final prediction is made by averaging the predictions of all trees, which reduces the risk of overfitting and increases accuracy.

In our study, we used a *RandomForestRegressor* from the *scikit-learn* Python library, a variant designed specifically for regression tasks. This model consisted of 70 decision trees (*n_estimators=70*), each independently trained to minimize prediction errors using the squared error criterion (*criterion='squared_error'*). The trees were allowed to grow as deep as needed unless limited by other parameters (*max_depth=None*), and splits were made with at least two samples (*min_samples_split=2*), ensuring each leaf node had at least one sample (*min_samples_leaf=1*). Additional features included sampling subsets of features (*max_features=1.0*, which uses all features for splits) and enabling bootstrapping (*bootstrap=True*), which trains each tree on a random subset of data with replacement. A fixed random seed (*random_state=42*) ensured consistent results across runs. These settings help balance flexibility and control in the model while maintaining its ability to generalize well to new data.

Once the models were trained, we used Shapley method to study the impact of each survey question response in accurately predicting the GPA (Li et al., 2024). Shapley method is a popular XAI approach rooted in game theory to help understand how much each feature (or input) contributes to a machine learning model's prediction. One can imagine the trained model as a "team" working together to decide, where each feature is a "player." The Shapley method fairly assigns credit to each feature by considering all possible combinations of features and calculating how much each one improves the model's prediction. This ensures every feature's contribution is evaluated in a balanced and unbiased way, regardless of the order they are considered. It provides valuable insights into which features are most influential, making complex models more transparent and easier to interpret.

Results & Discussion

We split our dataset into two partitions with students who have GPA 3.5 or higher and ones with GPA 3.49 or lower including 240 and 220 samples respectively. We trained two separate models, using the same random forest regressor as described above and applied 5-fold cross validation in each case where 80% of the dataset was used in training and 20% of the dataset was used in testing with alternating partitions and results reported as average of the 5 test partitions. The input consisted of individual responses to each survey question and the output was the associated GPA for each observation (i.e., student response). The performance metric used for the regressor was mean square error (MSE) calculated as the square of the difference between the GPA predicted by the model and the ground truth which is represented by the self-reported GPA.

It is important to note that for the Shapley method to provide a reasonably robust explanation, each model should demonstrate a similarly reasonable accuracy in predicting the output. This is not an exact science, and there is no specific threshold requirement beyond which the model output can be explained with Shapley, but at the minimum a convergence during training is necessary.

The best MSE for the first model (higher GPA cohort), after tuning several hyperparameters of the random forest regressor to predict the GPA, averaged across the 5 test folds, was **0.024**. For a practical interpretation, one can look at the normalized-root-mean-square (NRMSE) value, calculated by dividing the root-mean-square (RMSE) error (**0.15** in this case) by the mean of the GPA values in the dataset (**3.42** in this case), providing a dimensionless value that allows for easier comparison of error magnitudes across different datasets or contexts. The NRMSE helps contextualize the error relative to the scale of the data, offering a clearer understanding of the model's performance in predicting GPA, which in this case was approximately **0.044,** or **4.4%** - a reasonably low number which allows the model to be used in subsequent Shapley analysis.

Similarly, the best MSE for the second model, averaged across the 5 test folds, was **0.106,** slightly higher than the first model. However, the NRMSE value calculated by dividing the RMSE (**0.32** in this case) by the mean of the GPA values in the dataset (**3.42** in this case), still provided a reasonably acceptable **0.093,** or **9.3%** error metric which should allow the model to be used in subsequent Shapley analysis.

Figure 2 below shows two SHAP summary plots each corresponding to an individual model where the left plot is for high GPA and the right plot is for low GPA prediction models respectively. A SHAP summary plot visualizes the impact of each feature on the model's predictions across the entire dataset. Features are listed on the vertical axis, ranked by their importance, with the most influential ones at the top. Each dot represents a data point, and its position along the horizontal axis (SHAP value) shows whether the feature increased or decreased the prediction. The color of the dots indicates the feature value (e.g., red for high and blue for low).

Figure 2 provides interesting insights into how study habits and interventions impact students' academic performance. The most immediately visible observation is the dynamic range of feature impact for high GPA students compared to low GPA students. One interpretation of this is that the study habits students integrate into their daily lives seem to have a quantitively larger effect on their GPAs as their GPAs get higher – which would indicate a potentially more impactful implementation.

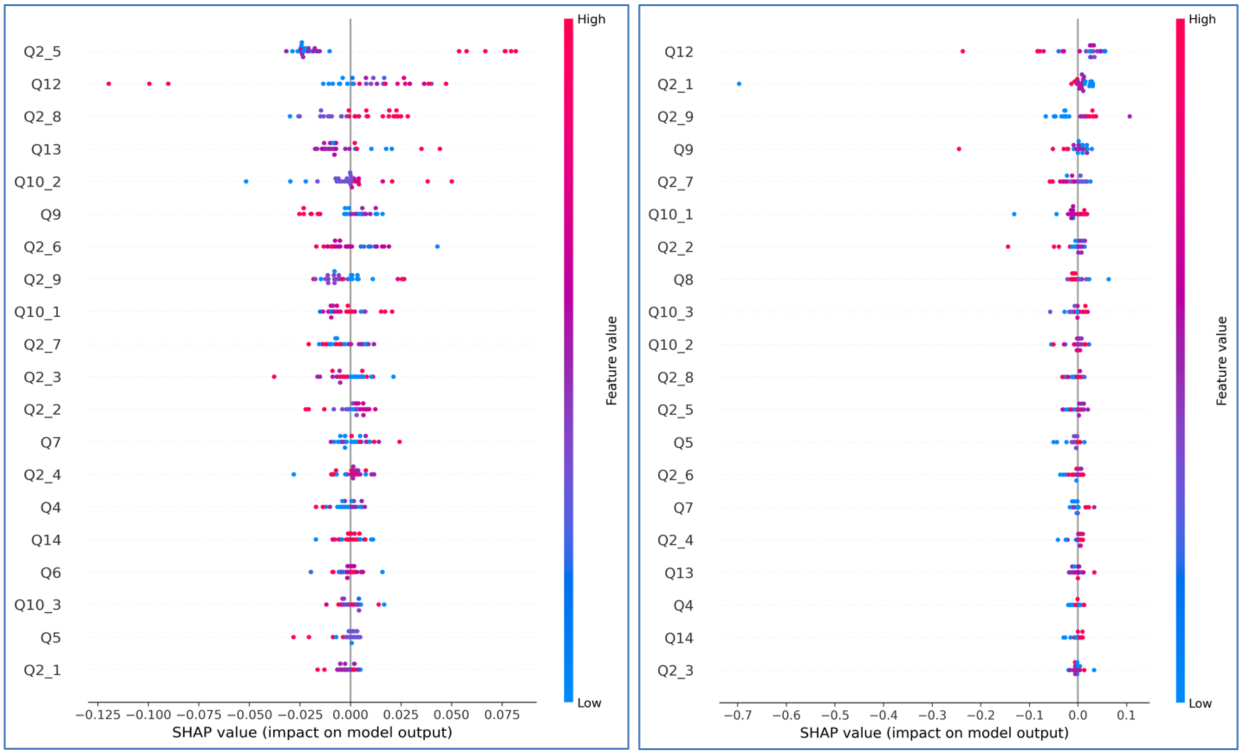

Figure 2. SHAP summary plots for high GPA (left) and low GPA (right) prediction models

One critical observation is the impact of the feature Q2_5, or the survey question which asks the following question: "Think about the last 30 days of the semester. How often did you do each of the following? ***I set study goals for the day***." For high GPA students, this is ranked as the most important feature and it is obvious from the plot that higher feature values (which indicate higher frequency of setting study goals and are represented by red dots in the summary plot) have the most significant positive impact on their GPA whereas for low GPA students the effect of Q2_5 is almost negligible (as it is ranked in the bottom 50% of the features in terms of importance).

One of the most critical features for the high GPA cohort is Q12 – which asks the following question: "***Which of the instructor strategies did you try*** (click all that apply)?" and records the total number of strategies they tried as the value of the feature. For high GPA cohort, higher values (again represented by red dots) generally tend to result in higher predictions in GPA whereas the effect for low GPA students is much noisier – which means the strategies they tried may not be making meaningful contributions to their GPA and academic performance.

Q2_8 provides another interesting observation – where the survey asks the question: "Think about the last 30 days of the semester. How often did you do each of the following? ***I studied with a friend***."**.** For the high GPA cohort, it is evident from the summary plot that the more times student engaged in studying with friends, the more likely they were to have a higher GPA whereas once again, for low GPA cohort this feature was ranked in the bottom 50% for importance.

The remaining features seem to have a mixed contribution to the prediction for both cohorts where for some students, higher feature values resulted in higher GPA predictions and for others lower feature values tended to do the same. One exception is feature Q10_2 which implements the question “How did you find action-state instruction? ***I am glad the EE department provided this instruction***.” where the positive responses were clearly associated with higher GPA predictions and vice versa for high GPA cohort with an inconclusive matching result for the low GPA cohort.

The Limitations of the Study, Insights Gained & Actions Taken

It is important to acknowledge the limitations of this study: i) there are no directly comparable studies, making it difficult to benchmark against existing literature, and ii) the sample size is limited, which makes it challenging to draw definitive conclusions. However, this limitation will be mitigated as more data is collected.

In terms of the insights gained, the authors acknowledge that some of the conclusions may seem intuitive (e.g., high-GPA students setting study goals for the day). Nonetheless, a very critical insight is the discrepancy in the return on time investment between high- and low-GPA students. More specifically, we observed that the low-GPA students struggle academically not necessarily due to a lack of effort but rather due to ineffective study habits and best practices.

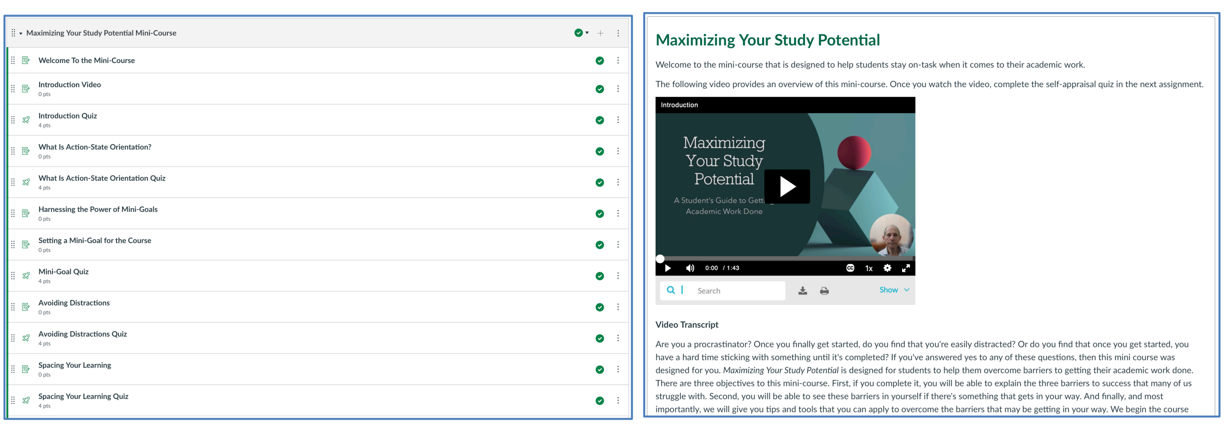

Figure 3. Maximizing Your Study Potential – CANVAS Module

In terms of the actions taken, as part of our efforts to improve student outcomes, we developed a mini course on CANVAS as a stand-alone module, designed to be integrated into all department courses (Figure 3). The mini course is designed with three primary objectives. First, upon completion, participants will be able to identify and explain the three common barriers to academic success that many individuals encounter. Second, they will develop the ability to recognize these barriers within themselves, particularly if such obstacles hinder their progress. Most importantly, the course provides practical strategies and tools to help participants overcome these challenges effectively. The course begins with an introduction to the concept of action-state orientation, which describes three cognitive tendencies that can impede goal achievement, both in academic settings and beyond. Currently, this module is offered as an optional resource. However, we have encouraged faculty to implement it universally, along with the strategies it highlights, to enhance student success.

Conclusions & Future Work

This paper describes an XAI approach using Shapley to explain how the action-state orientation and associated academic study habits impact performance for both high and low GPA students. By applying XAI to GPA prediction models trained on separate datasets, we identified the most impactful features, or responses to individual action-state survey questions, that contribute to academic outcomes. This comparative approach highlights how the importance of specific study habits differs in shaping academic performance across the two groups and proves our hypothesis which stated that the feature rankings of high and low GPA students will be different to potentially help provide actionable information.

For instance, setting study goals for the day seems to be the biggest predictor for academic success in high GPA students whereas its impact for low GPA students is inconclusive – indicating that it may be an unrealized potential gain for students who are struggling academically on which interventions can focus more. Similarly trying strategies for better time-management or studying with a group (or a friend) are robust predictors for higher GPA students with noisy conclusions for lower GPA cohort – indicating focusing on these areas for interventions could provide the biggest gains in academic success for the latter group.

In the future, we will continue to collect survey data from electrical engineering students (sophomore to senior) and study how the feature rankings change after students go through in-class or Canvas interventions with mini-courses on acquiring better study habits founded upon the theory of action-state orientation. Our next hypothesis will focus on whether low GPA students' survey responses become more robust predictors of their academic success (as indicated by SHAP summary plots) as they go through such trainings.

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