Integrated Closed-Loop Learning Analytics Scheme in a First-Year Engineering Course

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1 Abstract

This complete research paper works to tie the processes of identifying students that show signs of potentially being non-thriving at the end of the semester with a strategy to boost these students during the early part of the semester. The work in this paper, which applies the integrated closed-loop learning analytics scheme (iCLAS) that was used in previous similar studies at the University of Notre Dame, focuses on a general first-year engineering course. This paper follows the three phases of the iCLAS: (1) Architecting for Collection, (2) Analyzing for Action and (3) Assessing for Improvement. In the first phase, the course is designed and built to be able to capture the data needed to identify the students who show signs of being deemed non-thriving at the end of the semester. The second phase works to determine a method to identify these students who are deemed to be non-thriving at the end of the semester with just four weeks of course data. For the course highlighted in this study, the trigger was less than 80 percent on one-or-more of the first three homework assignments. The students are then notified and boosted with the aim of achieving improved learning outcomes for these students. Finally, the entire process is evaluated in order to determine the method's success. In this study, those students who responded to the boosting efforts achieved higher course performance than those who did not, demonstrating the benefits of conducting a boost effort.

2 Introduction

Identifying at-risk students is an established field of research in learning analytics [1, 2, 3, 4], whereas an emerging area explores the design of methods to boost student performance based on learning data analytics [5]. The goal of this study is to investigate both areas of research in order to boost students that are deemed to be at risk of being non-thriving at the end of the semester. To the authors' knowledge, current studies have not examined the evolution and evaluation of intervention mechanisms over the years when a course is offered multiple times. A possible reason for the lack of such studies is the problem of designing the required infrastructure to enable this analysis. The current study aims to show how the combination of learning data, identification of non-thriving students, and a means of boosting student performance can provide actionable insights on students who show signs of potentially struggling in a course early in a semester.

The University of Notre Dame, is a medium-sized (approximately 8,600 undergraduate students as of January 2020) private institution located in the Midwest U.S. The university has a 98% retention rate between the freshman and sophomore years. This retention rate, which is among the highest in the country, can make it a challenge to identify students who are not thriving as will be explored in this study.

This study focuses on the fall semester first-year engineering course (EG10111). This course is taken by all first-year engineering intents. The course's enrollment has been approximately 500 students over the past three years with typically a third or so of the students being female. The course is taught in multiple sections in order to maintain a high level of engagement between the instructor and students. Each section typically has between 35 and 48 students. More details about the course are presented later in this paper (Section 5.1.1).

This paper will discuss methodologies and best practices for capturing and analyzing course gradebook data, identifying students early in the semester who show signs that they may be deemed as non-thriving at the end of the semester, and boosting these students to achieve an improved academic performance.

3 Previous Works

Learning Analytics is a field based on technology-enhanced learning [6] that focuses on the learning process [7]. In particular, it can greatly shape and impact learning in higher education [7]. While learning analytics can be deployed on many levels (e.g. department and institution), the focus of the current study is on the course-level, which is concerned with learning analytics deployed in classrooms [8]. Learning Analytics has been popularly used in institutions for student success and intervention [9], with a comprehensive list of the use-cases given in Dietz-Uhler et al. [9].

Recently, there is a growing emphasis on closing the learning analytics loop [10, 11, 12, 13] in which the results of predictive analytics and insights gleaned from them are used to improve the current or next iteration of a course in the form of interventions [11] and learning design [14]. In particular, Clow [11] recommends a five step approach to this closed loop cycle: Capture, Report, Predict, Act, and Refine. The current paper illustrates how to use historical classroom data to improve identification of non-thriving students in the next iteration of the course, thus closing the learning analytics loop. A recent example of this effort is by Choi et al. [15], who identify at-risk students using a simple metric and provide interventions to those students in one small course. This methodology has been more recently employed in a first-year experience course at the University of Notre Dame [16] where they performed identification and intervention on the entire first-year body of students and repeated it for several semesters. This is the same technique employed in the current study.

Every learning platform/institute has its own data collection and storage systems, and attempts to standardize these have not been widely successful [17]. In response, the current work proposes a framework that can be tailored to build the underlying infrastructure, thus resulting in reproducible steps that can be implemented in any classroom setting in the future.

The first step of identifying students that need to be boosted, the non-thriving students of a course, has been a popular area of research in the learning analytics community [1, 2, 3, 4]. Different data sources like demographic data, students' performance, and behavior are used to predict at-risk students. Some of these studies show improvements in student's grades after deploying these systems [2]. But, it is not clear if the improvement in learning outcomes is because of the intervention provided or if there were other factors involved because of a lack of evidence [12]. While these studies focus on at-risk students, the authors of the current work find the use of this term misleading and potentially harmful as these students are not necessarily at risk of failing the class, but may struggle later or in other aspects of their campus life. In other words, the aim of the current study is not to help students survive, but to ensure that they thrive. It should be noted that in order to make this study repeatable at other universities by professors with variable levels of access to learning analytics data sources, the data sources in this study were limited to gradebook data collected through the course itself.

Once the non-thriving students are identified, various intervention strategies can be employed to improve the performance of these students. Some intervention strategies shift the effort to the students, with the system sending them an email [2], whereas other intervention mechanisms include intensive intervention within or outside the classroom [18]. Another commonly used approach is providing feedback to students using dashboards [19, 20, 21]. Rather than use the term "intervention", which can have negative connotations, this study referred to this process as the "boost". The boost strategy incorporated in the current work involves the use of an email communication to identified students. The correspondence, which is outlined in further detail in Section 6.2, also asks the students to create a customized, personal action plan. As noted above, this study (which was the first iteration of the boost for this course), focused on implementing methodologies that could be scaled to other universities by other professors. With this in mind, the boost was done in a way to create minimal extra requirements to students and course instructors.

4 Context and Framework

4.1 Research Questions

In order to evaluate the effectiveness of the current study, the authors focused on the following two research questions:

1. RQ1 (Identification Criteria): What metric can we use to identify students within the first four weeks of class that are deemed non-thriving at the end of the semester?
2. RQ2 (Intervention Impact): What is the impact of the boost on the student's performance in the course?

4.2 Our Framework

The paper is organized using the integrated Closed-loop Learning Analytics Scheme (iCLAS) developed by Syed et al [16] and shown in Figure 1. Section 4 (Architecting for Collection) describes the the first phase of iCLAS, which focuses on the "design", "build", and "capture" steps. Section 5 (Analyzing for Action) describes the methods used in the next three steps of iCLAS ("identify", "notify", and "boost"). Finally, Section 6 (Assessing for Improvement) concludes the iCLAS cycle by investigating the effectiveness of the method with the "evaluate" and "report" steps.

Following the work of Syed et al [16], the loop intersects in "evaluate" and "identify" steps to demonstrate that the processes of identifying the students that are deemed non-thriving at the end of the semester will continually evolve with each semester as the process is refined. With each

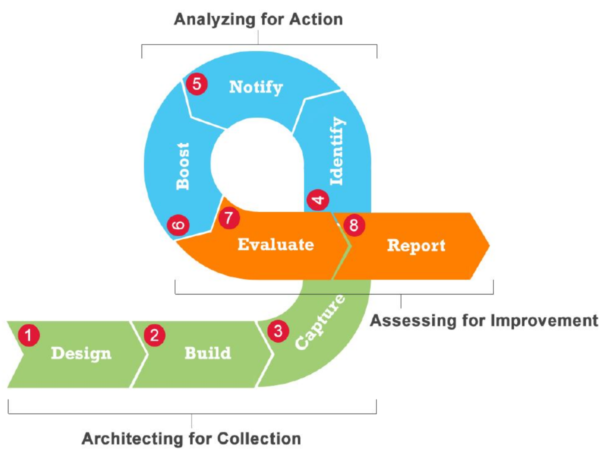

Figure 1. Integrated closed-loop learning analytics scheme [16].

semester, the information gleaned from the evaluate and report steps of iCLAS can be used to further refine the methods used to predict which students will be at risk of being non-thriving at the end of the semester.

5 Architecting For Collection

The first phase of the integrated closed-loop learning analytics scheme (Figure 1) is comprised of three steps: Design, Build, and Capture. The focus of these first three steps is to create a system that allows for the seamless collection of learning analytics data within the existing course layout that will be used in the remaining two phases of the scheme. In this study, the application of the iCLAS was with an existing course, which was already designed with active learning pedagogies in order to create an engaging learning environment. In an effort to make the process sustainable and repeatable by future users, the study built upon the existing course learning management system (LMS). The LMS automatically captures the relevant data that is used in the second phase of the iCLAS. These three steps enable this approach to be repeated by future courses while still enabling the relevant and necessary information be gathered.

5.1 Design

As the existing first-year engineering course that was the focus of this study was already collecting the data necessary for the second stage of iCLAS, the following section provides an overview of the course design, the assessment design and the standardized grading used in the course.

5.1.1 Overview of the Course Design

Students met in EG10111 sections for 75 minutes twice a week over the duration of the semester. The class sizes were limited to a maximum of 48 students and there were 12 sections of the course. The courses material was standardized between all the sections. In order to understand the method used to identify students to boost, it is important to understand the course structure and design. The course was divided into three modules. The first and third module were project-based and focused on the application of the engineering design process. During these two modules, the students also used the computer as a learning tool, with the first module focusing on Excel and the third module focusing on SolidWorks. The second module was focused on engineering major discernment through exposure to each engineering discipline offered at the university. For the first module, lectures consisted of both project-based concepts and Excel concepts. The Excel topics were taught using a flipped-classrooms with the students watching videos before coming to class. Class time was then dedicated to application of the skills in the videos led by the instructor and then led by the student through sample problems. The project completed through the first module was worth 15% of the course grade. The second module focused on engineering major discernment through department lectures, student panels, alumni panels and lab tours. The second module culminated with a discernment paper worth 10% of the course grade. The final module returned to the engineering design process through an iterative design. During this module the students learned computer-aided design (CAD) skills and then applied these skills to satisfy the project design statement. Students went through two cycles of the engineering design process and the module focused on the role of feedback as part of the second iteration. The project completed through the third module was also worth 15% of the course grade. Throughout the semester, homework assignments were used to reinforce the content covered in the course and were worth 15% of the course grade. Additionally, two exams were used to assess students individually at the middle and end of the semester. The first exam focused on the Excel skills learned in the first module and was worth 15% of the course grade while the second exam was comprehensive of the entire semester and worth 20% of the course grade. The remaining 10% of the course grade was based on participation, which consisted of pre-class quizzes related to the assigned videos in the first module and the completion of in-class activities and assignments throughout the course.

5.1.2 Assessment Design, Standardized Grading & Gradebook

To ensure consistency, all 12 course sections of EG10111 shared the same participation assignments, homework assignments, project and discernment paper requirements and exams. All of the course materials were distributed to all students from all 12 sections using a single Sakai course website.

Homework assignments were graded by the section's student assistant using detailed, standardized rubrics designed by the course coordinator to ensure consistency. The project and discernment paper rubrics were graded by the course instructors using standardized rubrics discussed at weekly instructor meetings. The first exam was graded by the section's student assistant using a detailed, standardized rubric created by the course coordinator, who also oversaw the grading process. Finally, the second exam was a multiple-choice exam and therefore standard amongst the sections. Therefore, despite the fact that each section was graded by its own instructor and student assistant, the students' grades were considered standardized and comparable across the 12 sections of the course.

Homework, participation, and exam grades were made available to the students through the Sakai LMS platform typically within a week of the due date. Grades on the other assessments were typically made available through Sakai within 10 to 14 days of the due date.

The design of standardized assessments, grading and course grade cutoffs allowed comparisons across the 12 sections of the course along with the ability to rapidly collect grade data necessary for the identify step in the second phase of the iCLAS.

5.2 *Build*

The structure of the course required a standardized LMS across all 12 sections. The EG10111 course used the Sakai LMS platform to accomplish this standardization. Sakai enabled a centralized location for students to have course-related materials, assignment submissions and grade information. Additionally, the Excel videos were integrated into the Sakai platform using the Panopto tool. This interoperability not only allows all course-related materials to be in a single location for the students, but also allows for a single location to gather course-related gradebook details. Furthermore, this approach required no additional changes to the course structure or additional requirements on the course staff or students, which is critical for the future adoption of such an approach by new courses.

5.3 *Capture*

For this study, all course data was captured through the Sakai Gradebook tool. While future iterations of this study may look into data sources such as activity on Sakai (logging in and out, clicking on resources, submitting assignments, etc.) or data related to watching the course videos, this first approach solely analyzed the course grades that were collected through the course gradebook. This approach was used for two reasons: (1) to simplify the first iteration of the study and (2) to demonstrate a technique that would be easily executed in other courses and at other universities. The data was also uploaded to Tableau in order to leverage its ability to create clear, concise reports for stakeholders involved with the process.

6 Analyzing For Action

Having designed and built a strategy to capture the data necessary within the context of the course, the study shifts toward the second phase of the iCLAS, which is to analyze the students to determine which students require an action. This process aims to boost students to have positive learning outcomes by first identifying which students should be boosted using historical learning data and trends to predict non-thriving students based on the student's grades collected in the first phase, notifying these students and then boosting the students. Similar to previous studies conducted in a general first-year course at Notre Dame, the messaging was crafted in order to avoid using negative language or words (such as "at-risk" or "intervention"), but rather more supportive, positive language was used (such as ""improve your performance") [16]. Finally, the students were boosted through the use of a personal action plan that was developed on an individualized basis based on the student's responses. The process was designed to be supportive and encourage the students to achieve higher learning outcomes.

6.1 *Identify*

One of the main tasks for the current study was to identify non-thriving behavior, or metrics, which consistently resulted in end-of-semester grades less than a B. These non-thriving metrics are what the authors refer to as triggers. The course-wide Sakai gradebook data was analyzed for the 2017 and 2018 fall semesters which have nearly-identical assignment topics and calendars to the 2019 fall course. The authors sought to identify a trigger that was: (1) consistent from year to year, (2) successful in identifying as many of the students with a final grade less than a B, (3) not too broad and therefore did not identify many students with a final grade greater-than-or-equal-to a B, and (4) located within the first four weeks of the semester. Identifying a trigger by the end of the first four weeks of the semester is much earlier than most previous works, and was motivated by the obvious fact that boosting students with non-thriving behavior earlier in the semester yields more time for them to make substantial adjustments for success. Specifically, identifying and boosting non-thriving students at the end of week four provides each of them with over a week to make changes before the first exam, which accounts for 15%.

The first step in this analysis was to manually calculate an adjusted final grade for each student. This adjusted grade only accounted for scores on each of the homework assignments and two exams. This adjusted final grade reflected each students' individual ability compared to the actual final grade which accounted for $\approx 50\%$ of group project work, the discernment paper, and participation points.

The analysis took a backward-design approach. One can phrase the problem for future semesters as such: at the end of the first four weeks of the course, we would like to have a gradebook trigger to identify students showing historically non-thriving behavior (i.e., students who are at risk for receiving a final course grade of a B or below). Analyzing the gradebook data for the fall 2017 and 2018 semesters was unique in the sense that the solution (i.e., the final grades) are already known. The authors used that to their advantage by looking for consistent gradebook metrics that resulted in low final grades. In total, there are eleven graded assignments within the first four weeks of the semester: three homework sets, four online quizzes covering material from the out-of-class video lectures, and four in-class participation problems. Nearly all possible combinations of triggers were explored. Traditionally, similar studies use zeros (i.e., no preparation) on any number of assignments to identify non-thriving students. This approach was also explored in this study; however, it was found to be too broad and only identified a small percent of students with a non-thriving final grade. Instead of this broad approach, course-wide assignment-specific and final grades were plotted, and general trends were explored. This analysis allowed for a customized trigger for our specific course layout.

The trigger which met the above criteria most consistently was: any students who received below an 80% on one or more of the first three homework assignments. 22/384 (6%) and 33/388 (8%) of the total students for 2017 and 2018, respectively, would have been identified as non-thriving under this trigger (i.e., received below an 80% on one or more of the first three homework assignments). The number was 28/406 (7%) for the fall 2019 semester. The average final grade for these identified students was 81.7% and 86.4% for 2017 and 2018, respectively, while the average final grade for the students not identified was 91.1% and 94.2%, respectively. These percentages were 84.5% and 91.8%, respectively for the fall 2019 semester, although it should be noted that triggered students in the fall 2019 semester were notified and boosted as discussed in following two sections. These results are tabulated in Table 1. 12/22 and 9/33 of the identified students each of the years received below a B for their final grade, which was the end-of-the-semester metric for non-thriving. That is to say that 12/22 and 9/33 of the identified students each of the years ended up with a non-thriving grade in the course (i.e., were correctly identified). This means that 10/22 and 24/33 of the identified students were incorrectly identified as non-thriving. Of the non-identified students, 22/362 and 6/355 ended up with a non-thriving final grade each of the two years.

Table 1. Results from non-thriving trigger data analysis.

Semester	# Triggered Students	Class-Wide Avg. Final Grade	Triggered Student's Avg. Final Grade	Non-Triggered Student's Avg. Final Grade
Fall 2017	22/384 (6%)	90.6%	81.7%	91.1%
Fall 2018	33/388 (8%)	93.5%	86.4%	94.2%
Fall 2019	28/406 (7%)	91.3%	84.5%	91.8%

The suggested trigger metric in the previous paragraph is not independent of the outcome variable (i.e., non-thriving final grade) because homework grades contribute to the adjusted final grade. In acknowledgement of this dependence and because both the criterion and the outcome are categorical variables, the authors used the Fisher exact odds ratio test. The odds ratio represents the odds that an outcome will occur given a particular exposure, compared to the odds of the outcome occurring in the absence of that exposure. For the current work, the odds ratio represents the odds that a student will not be thriving given they received below an 80% on one or more of the first three homework assignments, compared to the odds that a student will not be thriving given they did not receive below an 80% on one or more of the first three homework assignments. The odds ratio for 2017 and 2018 were 20 and 22, respectively. That is to say, in 2018, a student identified by the current trigger has 22:1 odds of having a non-thriving final grade compared to a student not identified. The null hypothesis of this test is that the criterion (i.e., trigger) does not affect the outcome (i.e., final grade). The results are presented in Table 2. The The null hypothesis can be rejected with a p-value < 0.005. Thus, it is shown that receiving below an 80% on one or more of the first three homework assignments affects the outcome of the students being identified as non-thriving by the end of the semester.

Table 2. Odds-ratio results from non-thriving trigger data analysis.

Semester	Trigger	Non-Thriving	Thriving	Odds Ratio
Fall 2017	$< 80\%$ on HW1, HW2, or HW3	12	10	
	$\geq 80\%$ on HW1, HW2, and HW3	22	362	20
Fall 2018	$< 80\%$ on HW1, HW2, or HW3	9	24	
	$\geq 80\%$ on HW1, HW2, and HW3	6	355	22

6.2 Notify

The students who met the trigger conditions after the first three homework assignments were graded were shared with the course coordinator. As part of the collaboration between the College of Engineering and the First Year Advising, the list of students was also shared with the first-year advisors.

Each student on the list was sent a personalized email from the course coordinator informing the students that after a recent grade audit, the course instructor wanted to insure that students were aware of the resources offered by the course due to their homework performance. The email also stated that in previous years, students who met the same trigger condition often exhibited similar trends in their In Class Exam. The email concluded with an invitation to fill out a personal action plan, which is explained in more detail in the following section. The email, which was written with feedback from the first-year advising staff and the course instructors and used language to ensure a supportive, assisting tone.

6.3 Boost

For the first iteration of the boost, the same approach that was used in the general first-year course outlined by Syed et al. [16] was applied to the first-year engineering course. The boost asked each student that was identified in step 4 to fill out a short qualitrics survey, which was referred to as a personal action plan. The survey first asked the students to identify the cause of the low homework grades. Using tree-based logic, the survey then led to carefully selected list of recommended action plan as shown in Figure 2. The students selected an action plan in order to help prevent low homework scores on future assessments. Using the qualtrics tool, the instructor was able to monitor which students completed the individualized personal action plan.

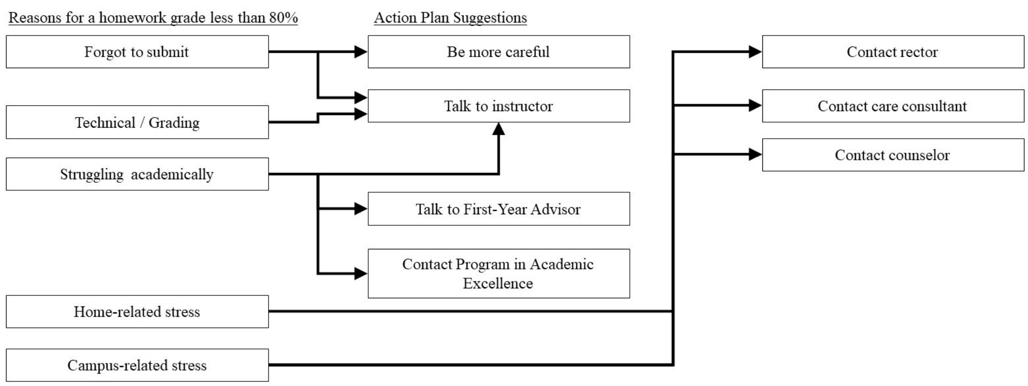

Figure 2. Bottom-up method of boosting non-thriving students [16].

7 Assessing For Improvement

The final phase of the iCLAS is to evaluate and assess the impact of the boost and report the results to the relevant stakeholders. The first step of the Assessing for Improvement phase is to compare the performance of the students who were boosted and developed a personal action plan to those who did not develop a personal action plan. Furthermore, both segments of students are compared to the group of students from 2017 and 2018 who would have been boosted. Finally, the information that is learned through the iCLAS cycle is disseminated to various stakeholders.

7.1 Evaluate

The first step in the Assessing For Improvement stage is to reflect back on the research questions from Section 4.1 in the context of the course design, boost strategy and relevant data collected through the course.

7.1.1 RQ1: Identification Criteria

The first research question focuses on the ability to reliably identify students within the first four weeks of the semester that are deemed non-thriving at the end of the semester. As outlined in

Section 6.1, through the analysis of data from the fall of 2017 and 2018, an identification criteria of a grade of less than 80% on one of the first three homework assignments in the course was selected. This identification criteria was shown in Section 6.1 to have an effect on the outcome of students being identified as non-thriving at the conclusion of the semester.

This section focuses on the analysis of the data from the fall of 2019, the data for which is shown below in Table 3. Before analyzing the data, one must consider a few important points. The first is that each year represents a different cohort of students with different experiences. This section will compare different years, but it is should be recalled that this is not the same group of students. Secondly, despite the fact that the course in its general form stayed the same throughout the three years, there was a new project introduced in the fall of 2019. While the project grades are not included in the analysis in Section 6.1, some of the concepts tested on the exams and homework relate back to the project. Finally, in the fall of 2019, the triggered students were boosted while the students in the previous two fall semesters were not. This has the potential to affect the number of students who met the trigger condition but were ultimately thriving at the end of the semester due to the presence of the boost.

Table 3. Trigger and non-thriving results from fall of 2019.

Trigger	Non-Thriving	Thriving
$< 80\%$ on HW1, HW2, or HW3	11	17
$\geq 80\%$ on HW1, HW2, and HW3	17	361

In the fall of 2019, approximately the same percentage of students were boosted (7%) as the fall of 2018 (8%) and Fall of 2017 (6%), demonstrating consistency of the triggered population size through each semester. Following the work done by Syed et al [16], rather than computing a simple accuracy from the data in Table 3 (which would be artificially high due to the small number of students who were non-thriving), Cohen's Kappa score, which is a commonly used approach for measuring inter-rate agreement, was computed. Ideally, rather than use the end-of-semester grades to determine non-thriving and thriving students in Table 3 (since the boost may interfere with their grades during the semester), the course grades through Week 4 would have been used to determine which students were non-thriving and thriving for the Kappa score. However, because of the limited grades through the fourth week and their correlation to the trigger condition, the non-thriving and thriving metrics used were based on the students' final adjusted grades. The authors deemed this as conservative because the boost is hypothesized to increase the percentage of number of students who meet the trigger condition yet were thriving at the end of the semester, which lowers the Kappa score. The Kappa score was 0.348, which is generally accepted to show fair agreement [22].

Finally, the percentage of the triggered students that were deemed non-thriving is analyzed. In the fall of 2017 and 2018, approximately 55% and 28% of the students who met the trigger condition were non-thriving at the end of the semester. In the fall of 2019, 40% of the students who met the trigger condition were non-thriving at the end of the semester. While this percentage is lower than the fall of 2017, it is higher than the fall of 2018. While one would think this percentage should be lower in the fall of 2019 than either the fall of 2018 and fall of 2017, since in the fall of 2019 the triggered students were boosted (and thereby should have had a lower percentage of students end up being deemed non-thriving), comparing the groups of students that responded to the boost to those that did not respond reveals a more thorough understanding of the impact of the boost. This is discussed in the following section.

7.1.2 RQ2: Boost Impact

The second research question focused on the impact of the boost. In evaluating the impact of the boost, four different populations of students were considered: (1) the students in the fall of 2017 that met the trigger condition but did not have a boost (as no boost was used in this semester), (2) the students in the fall of 2018 that met the trigger condition but did not have a boost (as no boost was used in this semester), (3) the students in the fall of 2019 that were boosted and developed a personal action plan, and (4) the students in the fall of 2019 that were boosted and did not develop a personal action plan.

For these groups, the mean and median adjusted final grades were calculated and are shown in Table 4. In order to ensure consistency between the semesters, these mean and median values were normalized by the average adjusted final grades in the course for all students.

Table 4. Impact analysis of boosted students.

	Mean	Median	# of Students
2017 - At Risk Without Boost	0.870	0.879	22
2018 - At Risk Without Boost	0.924	0.933	33
2019 - Responded to Boost	0.939	0.956	17
2019 - No Response to Boost	0.905	0.898	11

As seen in Table 4, the students who created a personal action plan (referred to as "responding to the boost") had the highest normalized mean and median adjusted final grade scores of the four groups considered. Furthermore, there was nearly a 4 percent difference between the students who responded to the boost in the fall of 2019 compared to those who did not respond to the boost in the fall of 2019. This suggests that those students who created a personal action plan (i.e., engaged with the boost) achieved higher learning outcomes in the course.

In addition to the analysis on the adjusted final grades, the overall final grades were also analyzed using the same four groupings of students. The mean and median values for the GPA and course grade along with the percentage of students receiving an A- or above for the three groups are shown in Table 5. Note that the the GPA and course grade values have been normalized with the average values for all students to provide a common comparison point across semesters.

The data in Table 5 reveals similar trends to the adjusted final grades comparison in that the students who responded to the boost in the fall of 2019 had the highest mean and median normalized GPA and course grades of the four groups. Notably, when comparing the non-normalized GPA values for the two groups from the fall of 2019 (which were normalized by the same value), the mean and median GPA for the group of students in the fall of 2019 that responded to the boost was approximately 0.15 and 0.34 points higher, respectively, compared to those students who did not respond to the boost in the fall of 2019. Finally, as noted earlier in the paper, one aim of the boost is to enable students to not only survive, but thrive. Students who

Table 5. Impact analysis of boosted students.

	Mean GPA	Median GPA	Mean Course Grade	Median Course Grade	Percent of Students Above A-
2017 - At Risk Without Boost	0.836	0.852	0.922	0.935	27
2018 - At Risk Without Boost	0.888	0.969	0.946	0.960	52
2019 - Responded to Boost	0.908	0.982	0.956	0.972	53
2019 - No Response to Boost	0.868	0.891	0.939	0.936	36

responded to the boost in the fall of 2019 were nearly 20 percent more likely to receive an A or A- than those students who did not respond to the boost.

7.2 Report

In the first iteration of the boost within the EG10111 course, reports were generated for the use of the course coordinator. The results of the boost will be disseminated with other course coordinators and first-year advisors. In future iterations of the boost, more extensive reporting will be incorporated, especially when more learning analytics data is collected and utilized (i.e., click counts, video streaming data, etc.).

8 Discussions, Conclusions, and Future Works

The work outlined in this paper built on previous work by some of the co-authors at the University of Notre Dame in studying the First-Year Experience course, a course required for all first-year students focused on a meaningful transition to college life. The course was studied over several semesters following the iCLAS. The effort demonstrated that in the course, students identified as potentially non-thriving could be boosted to achieve improved learning outcomes.

This study applied these concepts to a first-year engineering course at the University of Notre Dame. The nature of the course differs from the first-year experience course in its more technical nature. It therefore follows that the trigger used to identify students who were potentially non-thriving should have both an engagement element (i.e., are assignments being submitted?) and a technical comprehension element (i.e., are the assignments being completed correctly?). This differs from the first-year experience course that focused solely on the engagement element.

The study first demonstrated the ability to identify students students who had the potential to be non-thriving at the end of the semester based on the student's first three homework assignments (RQ1). While there were many false positives and false negatives due to the needle-in-the-haystack nature of the task, the odds ratios were comparable to the previous studies from the first-year experience course. While future works will continue to explore and evaluate new means to identify students within the first four weeks of class that are deemed non-thriving by the end of the semester, the identification of such students is a complex problem. This is compounded by the fact that the material, contexts or assignments that result in non-thriving results may not occur until later in the semester for some students. Future work will also focus on quantifying the number of students that are non-thriving at the end of the semester but do not exhibit signs of disengagement or confusion with course material until the later parts of the semester.

The study then demonstrated the ability to have a positive effect on the learning outcomes for students who responded to the boost through the development of a personal action plan (RQ2). Students that created personal action plans after being boosted had higher adjusted final grades (which isolated the individual components of the course grade) and final course grades on average compared to the students who did not create the personal action plan. Furthermore, the same students had higher adjusted final grades and course grades on average compared to the students who would have been boosted in the fall of 2017 and fall of 2018.

It is important to note that the methodology used in this study was designed to impose limited additional requirements on the students and course staff with the intention that other courses could similarly adopt the methods from this work. That being said, through partnership with other groups around campus, the authors intend to continue this effort, but also consider a larger data set when identifying future triggers that includes demographic information about the students and non-grade based engagement data sources such as click data, video engagement data, etc. This information, such as how frequently a student logs into the Sakai course site, may reveal different ways to identify students who have the potential to be non-thriving at the end of the semester.

There are also several other avenues for future research. One such avenue is tracking students in multiple courses simultaneously. By examining which students meet the trigger conditions in different courses, there may exist the potential to better understand the student's struggle. For example, if a student was found to be struggling in both the first-year engineering course but not in the first-year experience course mentioned above, this may indicate the student has remained engaged in the coursework but is struggling on the technical aspects of the engineering course. Another area for future research is determining approaches to engage those students who do not initially create a personal action plan. From the study, there was a difference in the learning outcomes between the populations who did and did not create a personal action plan. Therefore, further work can be conducted to determine methods to have students develop such plans. Finally, the nature of the boost is yet another area for future study. For a course that requires both engagement and technical understandings of topics, a boost that is more than just an email and the development of a personal action plan may enable more significant learning outcomes for the boosted students.

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