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The Value and Instructor Perceptions of Learning Analytics for Small Classes

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The Value and Instructor Perceptions of Learning Analytics for Small Classes

After the majority of education moved online during the COVID-19 pandemic, it became increasingly critical to gauge student learning and engagement without in-person interactions. Without the visual cues present in classrooms, instructors were blind to the nuances of engagement afforded by face-to-face instructions. Instead, instructors relied on student performances on assessments as the proxy or the lagging indicator for engagement. Learning analytics, on the other hand, provides an additional window into student engagement that is frequently underutilized. Learning analytics uses the data generated as the students interact with the learning management system (LMS) to augment instructor insights. Learning analytics has been often used to conduct predictive functions for student performance within massive open online courses. How can learning analytics assist instructors teaching smaller classes or even in-person classes? To investigate the value learning analytics provides, two fully online, small asynchronous engineering courses were studied retroactively. Aspects of student engagement and performance were analyzed for trends. The trends were then used to draw insights that can be used to improve the student experience for both in-person and remote settings. Secondly, recognizing the value of learning analytics, instructor perspectives were surveyed to gain useful insights on current practices and attitudes towards the topic. The results suggest that challenges exist for widespread adoption of learning analytics for typically smaller courses. Common hurdles were documented. The combination of the learning analysis and the faculty survey provide insights on the opportunities that exist as we continue to leverage the lessons learned during the pandemic. The exercise can also guide the development of effective online or in-person learning environments.

Introduction

In March of 2020, the educational landscape abruptly shifted from traditional, in-person delivery to online, distanced learning due to the COVID-19 pandemic. By the end of April 2020, 191 countries worldwide had closed their schools, impacting 1.5 billion students from pre-primary to post-secondary education [1]. Online learning is not a new concept, especially not in higher education. Massive open online courses (MOOCs) were first introduced in 2008 [2]. Online college educational offerings date back to the late 1980s, starting with the University of Phoenix [3]. However, these examples were not set up for the traditional college students who were on campus for a more intimate experience. Rather, the goal was to create an option for those who might not be able to attend classes face-to-face due to location or schedule to still pursue higher education [4]. Over the pandemic, all university students experienced online learning, not by option, but by necessity. This resulted in the largest group of online learners the university system had seen. The learning management systems (LMS) used during this time period collected vast amounts of data on individual students. While visual and verbal feedback that a classroom environment offered were lost in the switch to online, data quantifying student behavior on the LMS was readily available even for small class sizes. Through analysis, educators for these smaller classes have the potential to utilize this information to get a better sense of student needs and adapt coursework accordingly, similar to how MOOCs use this information more broadly.

Learning analytics (LA) is a growing field in educational research. LA is used by educators to make critical decisions about the educational experience for students. LA is commonly used to identify students at risk, adapt and tailor course content, and present recommendations based on student outcomes [5]. Institutions, students, and faculty are all stakeholders when it comes to LA [6]. Many applications of LA include the creation of a dashboard to show results and visualizations on the data collected. Some dashboards are designed specifically for students [7], but the majority provide performance and engagement metrics for the educator. The literature studies involving LA dashboards are frequently customized for the study and ask professors to utilize it and evaluate their usage. Dashboard components include student demographic data, past performance data, current performance data [8-10]. Sentiments regarding LA implementation are mixed. Many educators in the studies enjoyed having more insights given to them about their students, empowering them to focus their attention on students that needed assistance [8]. Passing grades improved when teachers used the systems, benefiting the student [9]. Despite the positive sentiments and results, there were also educators concerned about the lack of ease-of-use and potential major changes to their teaching methods [11]. Utilization of the system also decreased over the duration of the course. Not all features were used, and not many teachers attended the information sessions about the system prior to rollout [12]. Overall, we recognize the value of LA for both online and in-person classes where students are interacting with some content online. However, the outcomes of LA can be mixed depending on its use and implementation.

In some ways, educating the educators about the LA outcomes is important for its effective implementation. There is a need to overcome the negative sentiments towards LA and recognize the value-added to both online and in-person learning. We must also investigate the cause for the negative sentiments. Secondly, the majority of the studies focused on courses with large enrollments. Would the benefits also translate to smaller classes designed for more traditional on-campus students? Furthermore, many of these studies involved established online education programs. Students enrolled in these online programs are already familiar with online learning. On the other hand, most university faculty only recently made the transition to teaching fully or partially online delivery. These students and faculty are used to face-to-face interactions to inform their learning and teaching, respectively. How does LA augment in-person feedback? The combinations of these questions and gaps in literature informed the research questions for this study. This work attempts to answer the following questions for a traditional engineering program:

1. How much value learning analytics provides to courses with small enrollments?
2. What are faculty perceptions of the value gained from learning analytics?

To study the first question, two online asynchronous courses at Rowan University's Mechanical Engineering Department were studied. With enrollments of the students being less than twenty five, what conclusions can be made by studying the available learning analytics? The majority of the courses in this program are offered in-person with typical enrollments being 25-30 students per course. Therefore, the asynchronous courses studied were unique considering the typical student experience where face-to-face courses are the norm. These two courses were offered post-pandemic and provided the necessary data for LA to be applied to showcase the value gained retroactively to their offering. To answer the second question, the LA insights were shared with the faculty to capture their attitudes and perceptions towards LA. The combination of the insights gained by addressing the two questions above are captured in this work. The outcomes have the potential to inform future implementation of LA in regular courses and improve teaching effectiveness.

Methodology

To address the two research questions, this work was split into two stages. The first stage, *Course Learning Analytics*, involved applying LA to two existing courses and recognizing the potential insights. For the second stage, *Instructor Perspective Survey*, the LA results were then used to gather faculty perceptions on the value of LA to their courses. It was important to use existing courses at Rowan University's Mechanical Engineering program for LA to demonstrate its utility in making educational decisions that are localized to the institution.

Course Learning Analytics

Two recent courses were selected for developing the learning analytics (LA). Introduction to Thermal-Fluid Sciences (iTFS) taught over the summer semester and Introduction to Nanotechnology (Nano) is taught over the regular semester. iTFS is typically taken by rising mechanical engineering juniors; whereas Nano is an upper level technical elective targeted for both undergraduate and graduate students. The iTFS course is focused on developing analytical proficiency involving thermodynamics, fluid mechanics, and heat transfer concepts. Nano, on the other hand, is highly applied and primarily focuses on using mechanical engineering fundamentals to explore potential applications at the nanometer scales. The enrollment for the courses was as follows: iTFS $N = 18$ and Nano $N = 24$. Both courses were taught online asynchronously by the same instructor via Canvas LMS. The online format of the courses provided access to appreciable data to perform LA.

The primary student interaction data was obtained from the Canvas LMS system for both courses using the available .csv data files. This data was then analyzed and combined with student performance using common spreadsheet tools. Typical interaction data included cumulative time spent on LMS, page views, page views per week, and number of messages sent to or from the professor. A secondary source of data was from the Kaltura media player embedded within the Canvas LMS system. Kaltura is how students access pre-recorded lecture videos with Canvas. The Kaltura data files provided interaction data related to the lecture videos available to the students. Typical interaction data included number of plays, number of unique viewers, completion rates, video length, view timing, etc. Individual student based data was limited within Kaltura data files.

Instructor Perspective Survey

Upon applying LA to existing courses, the key insights were shared with the faculty in the program to capture their perspectives on the value provided by LA. The survey was also developed to capture faculty sentiments towards LA and probe what faculty use to gauge student engagement via the LMS. Participants only included the faculty members of the Mechanical Engineering Department at Rowan University. Most faculty participants had not taught an official online course besides the pandemic experience.

The survey was designed with Likert scale questions related to the four categories being investigated. The question response ratings ranged from 1 for 'strongly disagree' to 5 for 'strongly agree.' The faculty completed the survey in two parts. The first part (pre-LA) was designed to capture their current instructional practices. After the first part, the LA outcomes from the first stage of this work were shared with the faculty. The second part (post-LA) then captured faculty perceptions of LA for their courses.

(a) pre-LA survey

The pre-LA survey included two sections. The first section asked faculty about their current usage practices on the LMS.

1. I frequently use the gradebook feature to assess performance.
2. I frequently use the Canvas > People summaries to gauge activity.
3. I frequently use the Course Analytics function (during or after the course).
4. I frequently use the Kaltura media player analytics (during or after the course).
5. I frequently use other tools to conduct learning analytics. Describe the tools below.

The second section of pre-LA asked specific methods faculty use to gauge learning:

1. I conduct informal surveys to capture student experiences in my class.
2. I rely on student behaviors during class to inform my teaching.
3. I use informal interactions with students to inform my teaching.
4. I use attendance to assess engagement.
5. I use the student evaluations at the end of the term to plan my teaching.
6. I use traditional (direct) assessments to inform my teaching.
7. I rarely use any indirect feedback mechanisms.

Once faculty completed the pre-LA part, key outcomes of LA generated from the iTFS and Nanotechnology courses were shared. The goal with this step was to provide examples of what could be obtained from program-specific courses through LA.

(b) post-LA survey

After this brief presentation, faculty completed the post-LA part of the survey. The first section asked about faculty's thoughts on how useful LA would be to them and how they might utilize it in their courses.

1. I would use LA to identify students that are struggling.
2. I would use LA to identify students that are high performers.
3. I would use LA to examine topics that students struggle with.
4. I would use analytics to identify content that struggles to engage students.
5. I would use analytics to make improvements to the course content.

The second section of post-LA addressed any concerns or challenges the faculty had about LA in their courses.

1. The amount of information can be overwhelming.
2. The amount of time required to generate insights can be overwhelming.
3. The insights from LA are already available from in-person teaching.
4. The learning analytics insights can be inaccurate and misleading.
5. These efforts are not valued by my program.
6. The outcomes of LA will have minimal impact on my teaching.
7. The efforts go well beyond my job expectations.

Upon completion, the interviewee was provided with an opportunity to share their thoughts during the open discussion section. If they felt all of their thoughts were accurately captured with the survey questions, this part was omitted. However, if they had any additional thoughts, the audio was recorded to preserve their original words. The qualitative inputs were summarized for evaluation.

Results and Discussion

Course Learning Analytics

The first research question was related to the value provided by learning analytics to classes with small enrollments. The analysis began by first mapping the collected data to individual student course performance. Several dimensions were explored to reveal patterns and trends for individual students. As a start, cumulative analytics and student performances were studied. Cumulative data looked at the overall information accumulated at the end of the course disregarding its evolution across the term. The connections between cumulative analytics and student performance was too varied for the two courses studied. In other words, no clear or valuable trends emerged when term totals of page views, communication, or time spent on the LMS were mapped to individual student performance.

A more meaningful narrative of learning emerged with a more granular look into (a) Time Dependent domain with week-by-week evolution of learning analytics or (b) Content Dependent domain by studying how students interacted with video lecture content type. A decision was made to generalize the outcomes of learning analytics rather than focus on individual students. The aim here was to capture broad narratives about the two courses that can eventually help instructors when designing learning experiences for a broad audience. Thus the students from each course were grouped into quartiles based on their final course performance. The lower quartile consists of students in the 25% percentile, the upper quartile consists of students in the 25% percentile, and the middle quartile with the remaining students 50% of the students.

(a) Time Dependent Learning Analytics

The time dependent analytics involved studying how student quartiles mapped to the LMS interaction data. Student communication with instructors and time spent on the LMS showed limited trends to make any conclusions about the value of either. On the other hand, page view metrics suggested a broader trend that was specific to each course. Figure 1 presents week-by-week averages of page views grouped by student quartiles for (a) Introduction to Thermal-Fluid Sciences (iTFS) and (b) Introduction to Nanotechnology (Nano). Overlaid are the major assignment deadlines. Figure 1 shows that the upper quartile average page views for iTFS are generally higher across the term, as opposed to the average page views by the lower quartile. This is an expected outcome if one assumes pages views as a proxy for student engagement and thus performance. This trend is less pronounced for the Nano course, however, where the page view averages for different quartiles often overlap. A secondary trend is that the average page views spike right before a major assessment for iTFS. This, however, is not the case for Nano.

The average page views during the project phase is highly dependent on the type of the project assigned. The instructor's insight here is that for iTFS, the majority of the efforts relied on external resources, whereas for Nano, the majority of the project required interaction with other students and the resources embedded in the LMS. In other words, the Nano project forced students to interact with the LMS. Finally, both courses observed reduced average page views two-thirds of the way into the term. For instance, Week 7 for iTFS registered hardly any views. Similarly, for Nano the Weeks of 7 through 11 received lower page views.

How do the page view observations translate to potentially actionable items for the course? First, it is important to comment that the type of content can impact the interaction patterns of a course. High-achieving students often interact with content more often in more traditional courses, whereas that is not the case for non-traditional engineering courses. As a result, identifying struggling students can be challenging without recognizing the specifics of course type. For instance, iTFS is a highly analytical course requiring students to revisit problems from the past to study and practice for the assessment; while, Nano relies on conceptual content that only those struggling with the topic warrant a revisit. Secondly, by observing the average page views across the term instructors can explore ways to mitigate the lack of interaction during certain periods through the course. Is the lull in engagement, two-thirds way into the course, caused by the course structure, course content, or due to factors beyond the course itself? Are there ways to improve student engagement during that period? Regardless of the action pursued, such insights are rarely available from an in-person course unless specific and deliberate interventions are designed.

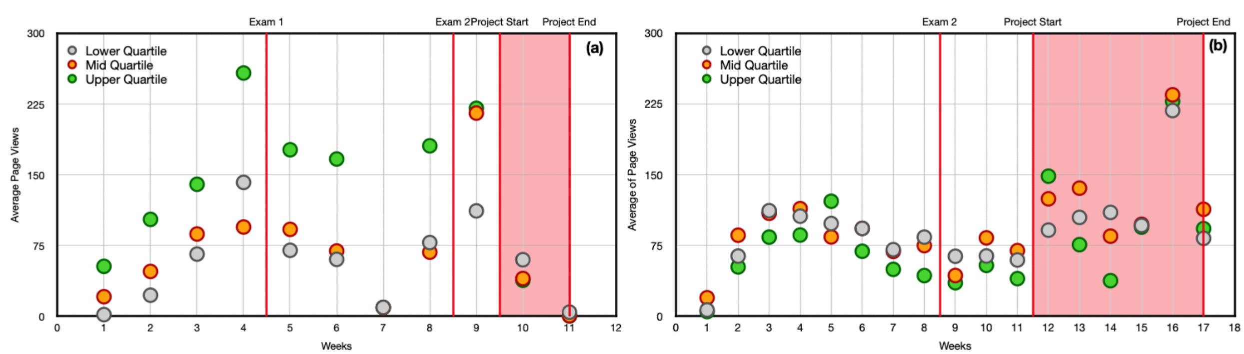
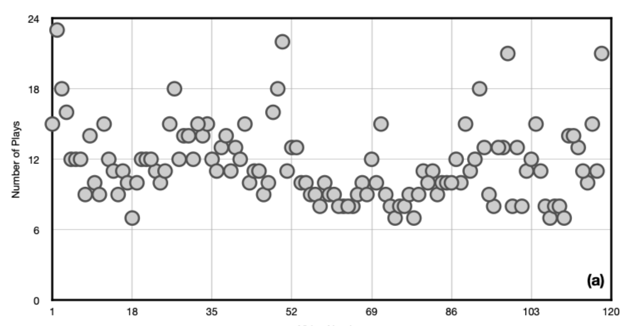


Figure 1. Average page views per week by student quartiles for (a) Introduction to Thermal-Fluid Sciences (iTFS) and (b) Introduction to Nanotechnology (Nano) course. Major assessments are highlighted.

(b) Content Dependent Learning Analytics

The video lectures are the primary content sources that students consume within both courses. While there are other content components such as assignments, textbook, and handouts, these were not studied here. By looking at how students consumed or interacted with the lecture videos, one can make some generalizations about engagement in each course. iTFS had 118 lecture videos and Nano had 31 lecture videos that students were required to watch through Kaltura media gallery. Each video was labeled numerically for this analysis. Figure 2 presents the number of views per video. Considering the number of students in each course were 18 and 24 respectively, there are videos that are played multiple times by students and there are videos that are skipped by some students. Overall, in Figure 2(a) for iTFS, the introductory videos and the videos related to the fundamentals of thermodynamic properties of water are played more frequently. The videos that regularly receive multiple views are the ones that present a calculation example. It is assumed that the students are reviewing how the problems are solved by the instructor to assist their own attempt at similar homework problems. It is also possible that students review the example videos that are directly connected to the upcoming exams. In Figure 2(b) for Nano, there is a gradual decrease in the number of views as the videos cover the fundamentals of material science up to video number 15. The views climb immediately when more applied content is discussed, ranging from materials characterization to synthesis. For Nano, there are no example videos where students have to refer back to how the instructor approached a problem. Therefore, the patterns observed here reflect the type of course content. Figure 3 presents similar data but now with views based on a unique viewer. These figures emphasize how only certain videos are viewed by all students, whereas some videos are rarely viewed by the class. For instance, introductory videos related to automotive engine cycles or their efficiencies are viewed only by a third of the iTFS course. Similarly, only half or less of the Nano class watched the course conclusion video. Recognizing these metrics about certain videos or topics can help inform the instructor where and how to re-engage the students.



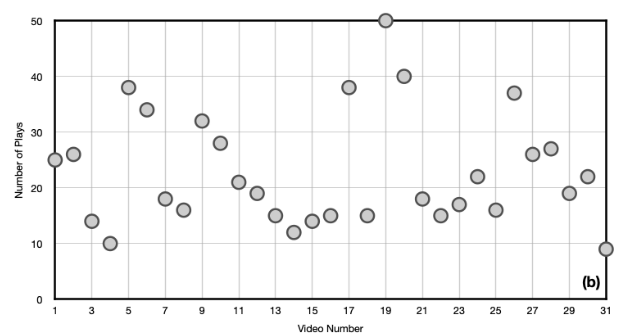


Figure 2. Number of plays plotted against lecture videos for (a) Introduction to Thermal-Fluid Sciences (iTFS) with 118 lecture videos and (b) Introduction to Nanotechnology (Nano) with 31 video lectures.

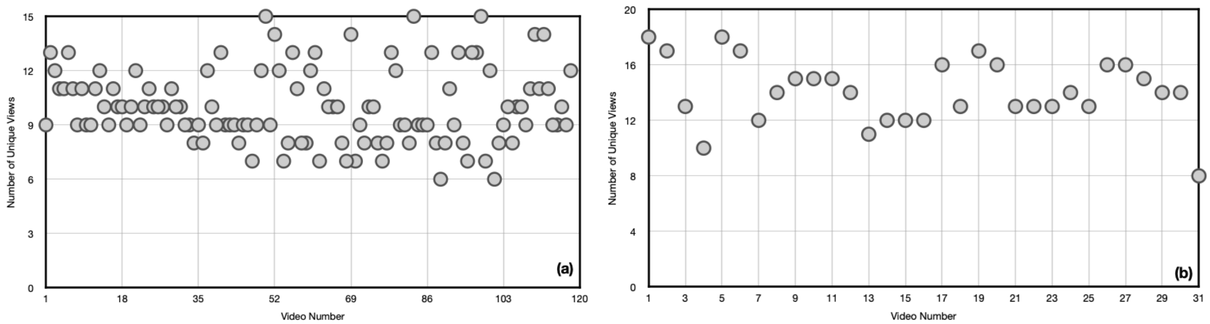


Figure 3. Number of unique views plotted against lecture videos for (a) Introduction to Thermal-Fluid Sciences (iTFS) with 118 lecture videos and (b) Introduction to Nanotechnology (Nano) with 31 video lectures.

Another way to quantify engagement with videos is to look at the average completion rates. To begin with, no correlation was found between the video length and the average completion rate. In other words, longer videos had almost the same completion rate as the shorter videos for both courses. Instead, a more granular look into completion rates by categorized video content provided better insights. For Nano, there was no easy way to categorize the data apart from sequential content build-up. For iTFS, however, there was an easy way to categorize the content for the seven chapters covered. For the iTFS course, the videos were categorized into three groups: Concept Discussion, Workout Examples, and Chapter Summary. Each chapter involved each type of video content in that sequence. Concept Discussion videos introduced and described the thermodynamic concepts and fundamentals. The Workout Examples videos showed the instructor solving a thermodynamics problem. The Chapter Summary videos reviewed all the concepts covered at the end of a topic. Figure 4 presents the average completion rate in percentage for each of the 118 videos in iTFS. The color coded data shows the type of content captured by the video. This visualization shows that the summary lectures routinely have lower average completion rates than the other categories of videos. It also shows a repeating pattern of the example lectures' completion rates increasing, hitting a peak, and then decreasing. This could be explained by students motivated to complete the videos when the topic is new. As the students gain mastery they tend to exit the videos sooner before completion. This trend deviates for the final chapter videos where multiple subsections and assignments break down the rise and fall trends. The forgoing observations yield multiple questions about the video lecture content. Are lecture summaries not helpful for students? How can we use the fact that example lectures are more frequently completed at certain times to better engage students? Example videos in general are viewed multiple times. How can we use that fact to our advantage in delivering important information? Should we place the most prominent information right at the beginning of the video in the case that students do not finish the video? There are numerous ways to make this information actionable and improve overall engagement. Such insights are difficult to capture with in-person courses. On the other hand, they are readily available for online courses. Armed with these insights, instructors can improve learning experiences that benefit students.

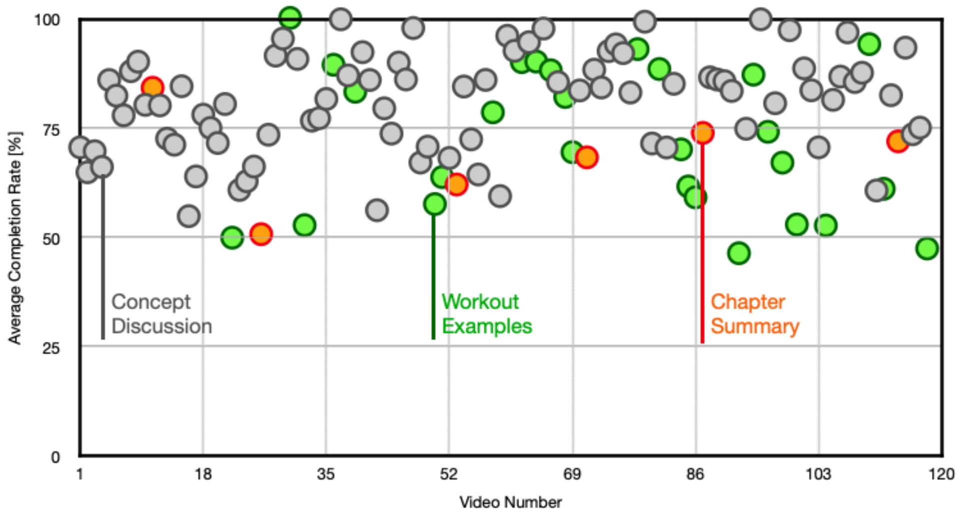


Figure 4. Introduction to Thermal-Fluid Sciences (iTFS) average completion rates categorized by video content: Content Discussion, Workout Examples, and Chapter Summary.

Instructor Perspective Survey

The second stage of this study focused on the second research question: 'What are faculty perceptions of the value gained from learning analytics?' To this end, eight Rowan University Mechanical Engineering faculty completed the survey out of the thirteen at the time of this study. All interviewed faculty teach at least one core mechanical engineering undergraduate course during the regular academic semester. None of the faculty, except one, have developed and taught an asynchronous course. The majority of the faculty interviewed teach multiple in-person courses per semester. Though the preceding analysis and insights relied on online courses, aspects of the insights also extend to in-person courses. As a result, the survey was designed to explore how instructors using all types of course delivery viewed the use of LA. Recall, the survey included two parts, the Pre-LA and the Post-LA survey.

(a) Pre-Learning Analytics Survey

For this part of the survey, faculty were asked about their current usage and practices on the LMS to gauge learning and engagement in their classes. This was before diving into the potential benefits of Learning Analytics, hence its title 'Pre-Learning Analytics Survey'. The aim here was to capture the baseline of standard practices. The survey indicated that the majority of the faculty use the gradebook function within the LMS. There was, however, an exception. One faculty did not use the gradebook function entirely. In fact, this individual refused to use any LMS services because of their comfort and excellence with analog systems. The faculty that use the LMS services indicated that they review time spent by students, as readily available on Canvas, but do not use that information directly as a student performance metric. Similarly, a majority of the faculty do not use any rudimentary course analytics or Kaltura media player analytics to evaluate engagement. This is expected considering that the faculty surveyed primarily teach in-person courses even though a few faculty indicated that some of their assessments and quizzes are embedded within Canvas LMS. When it comes to gaining student feedback, all faculty use informal methods. These can be either informal discussions, attendance, surveys, or classroom observations. All faculty use end-of-the-term student evaluations to plan for changes to the course. The described methods are reasonable with in-person courses where the face-to-face interactions dominate learning feedback. In general, faculty awareness and reliance on learning analytics through LMS was found to be low prior to this study.

(b) Post-Learning Analytics Survey

Next, the iTFS and Nano course learning analytics insights were shared with the faculty for this part of the survey. The aim was to gather feedback from faculty on the utility of similar learning analytics for their own future courses. The survey indicated that six out of eight faculty members surveyed felt they could use LA to identify struggling or high performing students. One faculty member, who does not use any LMS, did not see the value in LA's utility for this particular insight. The majority of the faculty, however, did see LA as a useful tool for identifying topics or content that students struggle with, and as a result make future improvements to the course. The faculty who never uses the LMS saw a marginal utility for identifying disengaging content. Overall, the results are expected considering the instructors surveyed relied overwhelmingly on in-person delivery of content and thus view such insights as supplementary to their existing methods. One can argue, however, that inferences such as the ones drawn from Figure 1 can be rather challenging to draw from an in-person course without considerable intervention.

The second aspect of this study investigated the perceived challenges of conducting and using learning analytics. When asked about the challenges of using LA for their courses, the survey indicated that all faculty thought that the amount of information available can be overwhelming and that the time to generate insights could be significant. Furthermore, some also felt the LA insights could be somewhat inaccurate or misleading; and the efforts would not be valued beyond the classroom. In short, there are valid and notable hurdles for adopting or incorporating some form of LA. On the other hand, a majority of the instructors felt that the insights from LA are not readily available from an in-person course. This is shown by Figure 5, which summarizes the responses for the rating survey question "The insights from LA are already available from in-person teaching."

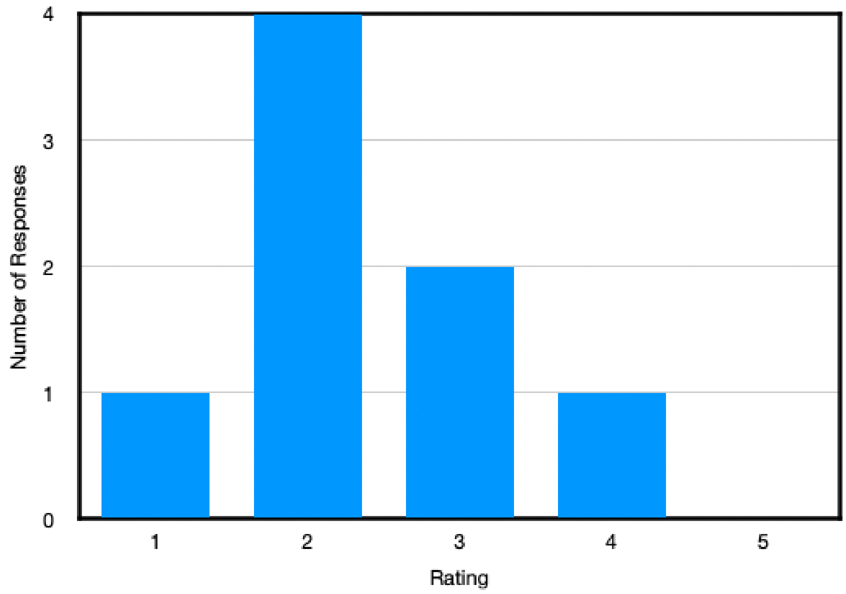


Figure 5. Faculty survey responses for the rating question “The insights from LA are already available from in-person teaching.” A rating of 1 represents “Strongly Disagree” and a rating of 5 represents “Strongly Agree.”

The final part of the survey was dedicated to open feedback allowing faculty share any LA-relevant ideas or ask for any clarifying questions. The two most discussed topics were a desire for more training on the LA features within Canvas LMS and a concern that these analytics do not show everything going on in the learning environment, especially when the courses are not fully online. The faculty reiterated that the insights captured may be helpful in some scenarios, but would completely miss out on offline interactions. In short, the faculty was interested in learning more about LA but also did not see it as the complete solution. These findings align well with other work on instructor usage and perspectives [13, 14]. On a broader scale, all the interviewees were unaware of the analytics that exist within their LMS platform and acknowledged that it is underutilized. These findings are likely representative of typical traditional in-person courses that increasingly use LMS for non-instructional purposes.

Conclusions

This work demonstrated that learning analytics has the potential to capture engagement patterns that are normally less discernible in an in-person learning environment. These insights can be used to better engage students and gain feedback in learning scenarios, especially where traditional verbal and non-verbal feedback is absent. LA can also augment in-person instruction by capturing student interaction with content placed on the LMS platform. Given the overall benefits of using LA, there are notable hurdles for its mass adoption by faculty. In fact, based on the survey of faculty at our program, it remains an underutilized tool. The results likely extend to many small classes offered by traditionally on-campus programs. Even though most courses utilize some form of LMS and thus the raw data already exists, the analysis and the subsequent inferences are not readily available to the instructors. The additional steps required to process the data is a major barrier for widespread adoption resulting in the potential benefits of the tool have not been currently realized by instructors. Learning analytics is yet another tool that faculty can use to shed light on potentially hidden trends within their courses, improving the experience for both students and instructors.

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