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Data-Informed instruction: pedagogical responses and obstacles in using learning analytics

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Abstract: E-learning resources and educational technology are increasingly used in STEM education, generating vast amounts of student-level data. Learning analytics tools can utilize this data, enabling instructors to adjust their pedagogy to support student success. Despite the potential benefits, the implementation of learning analytics does not always lead to improvements in teaching practices. This paper, through two case studies, investigates challenges instructors may face in adopting learning analytics. In Case Study 1, we examined how online activity data reflects student engagement by analyzing historical data from a learning management system (LMS) alongside observations of class schedules. Online activity was compared to semester timelines and qualitative codes to identify patterns of alignment. The findings suggest that accurate measurement of engagement requires the integration of both LMS data and contextual classroom information. In Case Study 2, we explored how learning analytics influences pedagogical change through surveys and interviews with instructors. Instructors generally found static data related to enrollment and academic standing more useful than dynamic data capturing students' online behaviors. The difficulty in translating data into actionable pedagogical strategies rendered the learning analytics less effective for long-term course-level improvements. The case studies highlight both the challenges and potential of learning analytics in STEM education. Effective learning analytics intervention requires integrating qualitative insights, fostering collaboration, and providing targeted professional development to support evidence-based teaching and learning strategies.

Introduction

Higher education institutions are struggling with the decline in a key metric of retention rates [1]. Student attraction, persistence, and retention have been particularly problematic in STEM programs, with many STEM entrants switching to non-STEM fields or even dropping out of college [2]. The pandemic has also had a negative and potentially lasting impact on enrollment and retention [3]. Despite challenges to the traditional education format, we have witnessed a sharp rise in online and distance education over the past decade [4] and colleges and universities are making efforts to build hybrid campuses, especially after the pandemic [5]. However, the transition to online learning could potentially cause declines in student engagement [6], highlighting the need for supportive strategies employed by instructors and universities [7].

On the bright side, the proliferation of digital traces is paving the way for educational data mining and learning analytics and shows promise in enhancing academic success and retention by identifying at-risk students and personalizing learning experiences [8], [9]. With the widespread use of educational software and e-learning resources, large repositories of educational data are rapidly created. Researchers argue that by leveraging this data, tools such as learning analytics could bring significant benefits to students, instructors, and administrators in STEM programs [10], [11]. Despite potential benefits, empirical evidence supporting the feasibility, effectiveness, and generalizability of interventions is still lacking. Literature has suggested that more research into the implementation and evaluation of scientifically driven analytical interventions is needed to build a solid evidence base to support the long-term and sustainable utilization of educational data [12].

One long-standing concern of learning analytics is whether student engagement could be effectively captured through digital traces. Student engagement is a multifaceted concept that involves the time and effort students invest in their studies and how institutions support these efforts [13]. Learning analytics usually assess engagement through data collected from Learning Management Systems (LMS), which track students' online activities, such as the number of interactions, clicks, and time spent engaging with course materials. It is plausible that these metrics could provide insights into how students' efforts in class correlate with their academic success [14]. There is limited research on measuring the multifaceted engagement in online learning through learning analytics [15]. In addition, the transfer from instructors' understanding of data metrics to changes in teaching practices is a complicated process not adequately examined in the literature [16]. Instructors could face an initial learning curve when seeking and making use of relevant information from learning analytics [17]. Incorporating pedagogical decision-making into the system design becomes a significant research gap impeding effective learning analytic intervention for STEM education [18], [19].

The study seeks to address the research gap and advance our understanding of learning analytics through two case studies. In Case Study 1, we focus on evaluating whether online activity data collected through the LMS can serve as a proxy for measuring student engagement. In Case Study 2, we aim to understand instructors' perspectives and experiences of implementing learning analytics in their teaching through surveys and interviews. These case studies provide insights into the pros and cons of using online activities as a proxy for student engagement and shed light on instructional and institutional efforts for effective implementation of learning analytics in STEM.

Case Study 1: Online Activity and Student Engagement

Background

In recent years, there has been a noticeable decline in student engagement in postsecondary STEM education, a trend that was exacerbated during the COVID-19 pandemic. As campuses closed and institutions pivoted to remote learning, both academic and social engagement suffered. Research indicates that students' sense of academic engagement diminished when they felt socially or emotionally isolated during this period [20]. Even after many institutions reopened in 2021-22, faculty members observed continued challenges in re-engaging students [21]. As colleges and universities strive to recover from the pandemic's effects, they are beginning to uncover the factors contributing to this diminished engagement.

Student "engagement" is hard to explain and often is left undefined, making it even more problematic to know how it has changed over the past several years [20]. The dimensions typically associated with "engagement" are cognitive, behavioral, and affective [23], which are not typically captured by learning analytics. Nonetheless, learning analytics can provide insight into classroom activity, which can boost success and mitigate failure for students' academic success [24]. Analysis of behavior-based engagement in a classroom, although only one dimension of student engagement, is likely the most controlled by the instructor [25] and potentially the easiest to respond to with pedagogical changes.

By comparing online activity data from LMS platforms with qualitatively coded activity types, this study seeks to provide a nuanced understanding of how these metrics may reflect fluctuations in student engagement. Specifically, this case study was guided by the following questions:

- What can we know from student engagement from online activity data?
- How do qualitative observations of class activities align or misalign with online activity data?

Method

The site location for this study was a large research-intensive university in the mid-Atlantic region of the United States. This study was a single, instrumental case study, bound and limited by the students enrolled in the identified course during the specified semesters. We received approval from our institutional review board for an exempt, non-human subjects study and requested historical data from the LMS for the selected class and semesters. Data variables included starting and ending GPAs, starting number of credits earned and academic standing (i.e., junior, senior), and status of enrollment in the class (i.e., enrolled, dropped), and other de-identified students' demographic information. The online activity data records students' frequency of interacting with LMS and other related digital learning applications on a daily basis.

The selected class is an advanced-standing undergraduate course in psychology, designed and taught by the same instructor during Fall 2021, 2022, and 2023. The instructor confirmed no major revisions were made to the course during these semesters, which provides a level of consistency for us to review and compare data points. Three undergraduate teaching and research assistants coded each class as different types of activities (i.e., quiz, assignment) based on the information in the syllabus, LMS, and the faculty's reflection on in-class activities (ICAs). Both the syllabus and ICAs are provided by the instructor. These activities were coded by following the National Survey of Student Engagement (NSSE) engagement indicators. While NSSE is typically a student-taken survey, these codes provided one way for us to deductively organize the types of activities taking place in the classroom and to further contextualize the goal of the activity. We only used engagement indicators for which we felt we could know and align with activities, which included Higher-Order Learning, Reflective & Integrative Learning, Learning Strategies, Quantitative Reasoning, and Collaborative Learning (see [26] for detailed definitions of each code).

Results

Sample Student Population

More women enrolled in this course during fall 2021, 2022, and 2023 than men (65%, 70%, and 68% respectively), and more white students enrolled in all three semesters (52%, 48%, and 50% respectively). Most students were 21 years of age (50%, 49%, and 48% respectively), which makes sense as this course is for advanced standing students; overall, 62% of the students enrolled were classified as seniors. Students' residency changed over the three semesters, with an increase in out-of-state students, from 39% to 50%. In all three semesters, 20% or less of the students were identified as first-generation college students, and only one student during those three semesters was identified as a veteran. The starting cumulative GPA increased from 3.12 in 2021, 3.13 in 2022, to 3.32 in 2023. Overall, 35% of the students received an A or A-, 30% received a B+, B, or B-, and 16% received a C+ or C, demonstrating that most students pass the course in any given semester, with only 7% failing the class and 11% not finishing (as indicated by a late drop, unknown, or withdrawal grade status). On average, each semester had a total enrollment of 46 students.

NSSE Codes

Table 1 summarizes the number of NSSE codes in each semester, grouped by ICA and syllabus. Collaborative Learning was the most frequently coded item, as it related to the in-class discussions, in-class activities, and exam reviews, whereas the fewest coded indicator was quantitative reasoning. Since this course is a psychology course, more focus was placed on reading and group discussions than on calculation or quantitative analysis.

Table 1. NSSE codes frequency by semester and data source.

Semester	**2021**		**2022**		**2023**	
Data Source	**ICAs**	**Syllabus**	**ICAs**	**Syllabus**	**ICAs**	**Syllabus**
Collaborative learning		40		41		40
Higher-order learning	13	17	3	13	3	12
Learning strategies	1		2		2	
Quantitative reasoning	2		2		3	
Reflective & integrative	5	5	7	18	5	14

Online Activity Indicators

The trends of online activity indicators, along with the NSSE codes, are illustrated in Figure 1 and Figure 2. Generally, students' online activity increased on days with a planned activity (as indicated by NSSE codes) than on days without a planned activity. The differences are significant as suggested by the ANOVA test ($F_{(3,387)} = 33.31, p < .001, \eta_G^2 = .21$). For example, Figure 2 shows noticeable spikes on Nov 7, 2022, and Nov 6, 2023, in the online activity. These spikes are associated with collaborative learning but potentially also with the exams scheduled for four days later. The difference in average activity levels between different NSSE codes is not significant.

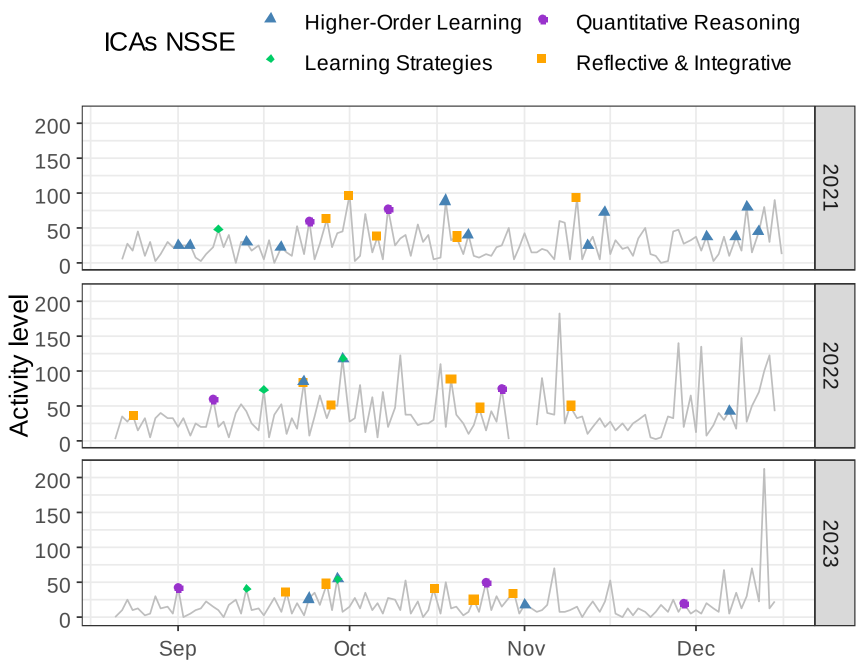

Figure 1. Line graph of online activity with ICAs marks.

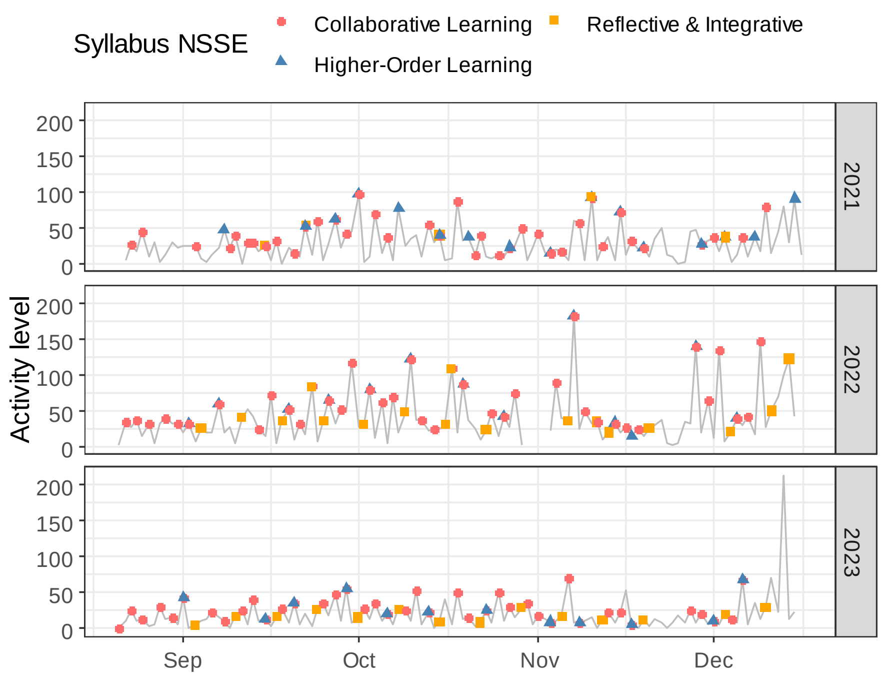

Figure 2. Line graph of online activity with syllabus marks.

Online Activity and Student Background

Results of the regression model of online activity levels on student background data are shown in Table 2. It is suggested that students with higher cumulative GPAs at the start of the semester, women students, and older students are more likely to report a higher level of online activity.

Table 2. Coefficients of online activity regression model.
(Significance: *: <.05, **: <.01, ***: <.001)

Variables	**Beta**	**95% Confidence Interval**	**p-value**	
Semester				
2022	334	137, 532	0.001	**
2023	223	22, 424	0.030	*
Start Cumulative GPA	273	103, 443	0.002	**
Start Cumulative Credits	-4.5	-8.8, -0.16	0.042	*
Semester Total Credits	-1.8	-33, 29	0.908	
Gender				
Woman	220	37, 403	0.019	*
Age	135	53, 216	0.001	**
Residency				
Out of State	127	-53, 307	0.166	
First Generation Student				
Yes	124	-89, 337	0.252	
Veteran Status				
Yes	-811	-2,384, 761	0.309	

Discussion

Measuring student engagement from collected online activity data

Our data show that students with higher cumulative GPAs in the semester, women, and older students, have higher levels of activity. While the higher GPA suggests students have a strong academic record, the age and gender might mean something different. Struggling students might review the content more, or make more attempts at the quizzes, increasing their online activity, even when the final scores are high. Additionally, uploading an assignment completed offline would show decreased online activity than a student who is completing the assignment in the LMS, yet no distinction is made in the data differentiating these factors. In this sense, any analytics outside of the assignment submission may not be useful in determining student engagement.

We saw spikes in activity, and while the course content did not change, the reason is unknown based on the available data. Perhaps the lecture changed slightly from last semester, or the students were more interested in the topic than other semesters; in other words, what happened in the environment is an unknown influence on the output [27]. Based on this, we believe it is not possible to use online activity as a basis for measuring student engagement. Rather, we argue that online activity, such as these data, measures a form of student involvement. These data do not show student motivation for activity, which is a component of student engagement.

Online activity changed by semester

The results of online activity show that student involvement changed over the three identified semesters, though not in the way anticipated. Activity was higher in 2022 than in 2021 and 2023. However, these data points must be used with caution. Students can select one of three paths (reading quizzes, discussion posts, or research paper), and there is no way to identify which path the students choose in the data. When looking at online activity data points, it stands to reason that those students who selected the research paper will have far fewer online activities than those students who are taking or retaking reading quizzes or posting and responding to discussion boards. These data points will show fewer online activities, but that should not be interpreted as lower "engagement." The instructor described mandatory office visits for students who selected the research paper. Arguably, the presumed time spent with the instructor, finding resources, and cognitive development to complete the research paper is an example of several academic challenges identified by NSSE but not captured in the LMS. This example of data shows the difficulty in using online activity as a sole measure of student engagement, as it removes the environment and does not provide a complete picture of students' activity.

Understanding how to use online activity data

The data show an uptick in online activity when a classroom activity is planned, as opposed to when there is no scheduled class activity. Online activities respond to the type of classroom activity based on the NSSE codes. This finding suggests that instructors interested in creating more online activities or using learning analytics should also think about how to connect learning analytics with the in-class activity in some way. In doing so, the instructor constructs the environment as an influencing factor in students' outcomes.

A possible use for these learning analytics data could be for individual student performance, as the aggregated broad strokes of the online activity show how involved students are from semester to semester. These data points could be used as a comparison for when assignments or course redesigns happen. When an instructor redesigns a lesson, assignment, or course, the instructor manipulates the environment to improve the students' outcomes. Over time, patterns in students' inputs that lead to different interventions may become evident. Overall, the individual counts of online activity are only useful when used in combination with other student-level data points, such as class activity, course design, and learning objectives.

Case Study 2: Instructors Making Sense of Learning Analytics

Background

Instructors can use the data to reflect on their teaching practices, potentially influencing instructors' pedagogical decision-making [28], yet the willingness to act on the data is minimal [29]. As Guzmán-Valenzuela et al. [30] pointed out, the data presented by the analytical tool may not necessarily align with actual student learning. The complicated learning contexts may not be thoroughly considered in the data analysis. Moreover, in the one-sided data-driven tool where students are not involved or privy to the output, data are disconnected from the context, which makes it hard to understand the students' perspective of the data representation [31]. Challenges such as these might be partially attributed to the differences between the data-driven analytics community and the applied teaching community, which may not always work collaboratively to develop the tools and implementation strategies.

Poquet [32] proposed that sensemaking in learning analytics allows for reference to the cognitive processes of identifying the properties of an object and understanding the potential actions or opportunities. Li et al. [17] unpacked the instructors' sensemaking process by identifying three types of questions they developed: goal-oriented, problem-oriented, and instruction modification. Wise and Jung [33] conceptualized instructors' process of analytics use through the triangulation and contextualization of multiple data sources, which were translated into whole-class scaffolding, targeting scaffolding, and revised course design. We define sense-making as the focused attempt to identify problems, make connections and explanations, predict future outcomes, and recognize interventions for change. Guided by the work of Wise and Jung [33], the current study explores instructors' experiences with a classroom data analytics intervention and focuses on instructors' strategies and hesitations when and how to use data to support instructional decision-making. The mixed-method research design based on existing literature seeks to answer the following research questions:

1. How do instructors make sense of the different data provided by the analytical tool?
2. How do instructors incorporate their understanding of data into pedagogical actions?
3. What are the challenges to instructors' effective adoption of the analytical tool?

Method

This study was conducted at the same institution as that of Case Study 1. We sought to understand the use of an internal classroom analytics application (Course Analytics), which aggregates data from the Learning Management System (LMS, e.g., Canvas), the student information system, and other vendor learning applications such as Top Hat[1]. Course Analytics, an internally built application, combines and visualizes data to help instructors make operational decisions about how to best support students in their classes. While these data are accessible to instructors through other means, Course Analytics compiles the student-level data into a single location. Privacy and ethical considerations were centered on the development of Course Analytics, with approval from the University Registrar and the University Privacy Office.

Data Collection

After approval by the university's Institutional Review Board, we sent an online survey to instructors currently using the Course Analytics intervention. The survey contained 22 items, covering the instructors' background, course information, and their use and feedback of the tool. The survey was a demographic understanding of the instructors using the application, including typical class size, student-level taught, and self-reported use and knowledge of educational technology in the classroom. At the end of the survey, we invited respondents to sign up for an interview. The semi-structured interview was guided by 14 main questions that probed instructors' motivations, experiences, and critiques of using the data. For example, we asked instructors about the type and size of classes typically taught, how frequently they used Course Analytics, "What is your primary goal for using this data?" and "In what ways has the tool changed your teaching or approach for the semester?" The interviews were mediated and recorded through Zoom, a video-conferencing software. The audio recordings were transcribed, cleaned for clarity, and analyzed through a shareable spreadsheet.

This study was descriptive and exploratory based largely on qualitative data from the survey and interviews. We used purposeful sampling for this study, ensuring participants had the right knowledge of the tool [34]. At the time of data collection, 126 instructors were identified as active users of the tool.

Data Analysis

Interview transcripts and open-ended survey responses were analyzed through a hybrid inductive and deductive thematic analysis process. Three researchers went through multiple rounds of coding and discussions together to interpret the data and identify themes. The first round of coding established an initial codebook by adapting a model of instructors' process for using analytics from Wise & Jung [33], which contained a two-part structure of sense-making to pedagogical response, with elements of interpreting data, taking action, and checking for impact (p. 56). Each researcher independently read and coded one-third of the dataset. Then, researchers collectively discussed the coding results to evaluate how well the data fit in the initial frame and proposed revisions to the codebook. For the second round of coding, the researchers followed the revised categories and developed new categories and subcategories when necessary. In part, the researchers needed to account for users' potential improvements and ideas for the application. Analytical memos were used throughout the process to augment coding and reflections [35]. Researchers met periodically to compare and refine their interpretations of the categories. In the last round of coding, the primary researcher reviewed all data analysis results and documentation to extract six themes (Table 3), merging the interpretations from all researchers and developing them into the final narrative.

As this study combines survey and interview data, we assigned pseudonyms for each group, designating "I" for interview participants and "S" for survey respondents, and added a number for clarity.

Table 3. Themes and code frequency emerging from thematic analysis.

Themes	**Descriptions**
Usage motivations	Reasons why instructors choose to integrate Course Analytics into their class and teaching practice
Sub-topics	Beliefs in the potential improvement of class General interest in and curiosity about technologies The ability to know more about students The convenience of having a one-stop shop for data
Data interpretation	Instructors' data interpretation patterns
Sub-topics	Compare and reference external information Get a holistic view of class makeup
Pedagogical response	Pedagogical actions promoted by the use of Course Analytics
Sub-topics	Class scaffolding Concurrent class coordination Curricular planning Discussions with colleagues and students Individual student support Subgroup student support
Usage obstacles	Issues preventing instructors from taking full advantage of the tool
Sub-topics	Applicability in different classes Data accuracy concerns Data cannot represent engagement Difficulty in data interpretation Lack of experience in usage No need for extra tools Uncertainty on actionable items
Improvement suggestions	Additional features that could make data more useful to instructors
Sub-topics	Improvements in the user interface More diverse categorizations of student subgroups More thorough training programs for data intervention
Ethical concerns	Ethical concerns in using data and the future development of tools
Sub-topics	Potential risk depending on the individuals Privacy-utility trade-off in learning analytics

Survey Results

In total, we collected 26 valid survey responses (S1 - S26), which represent around 21% of registered users. Instructors estimated that they spent most time leading lectures (35.7%), small group or lab activities (25.5%), and class discussions (17.3%) (see Figure 3).

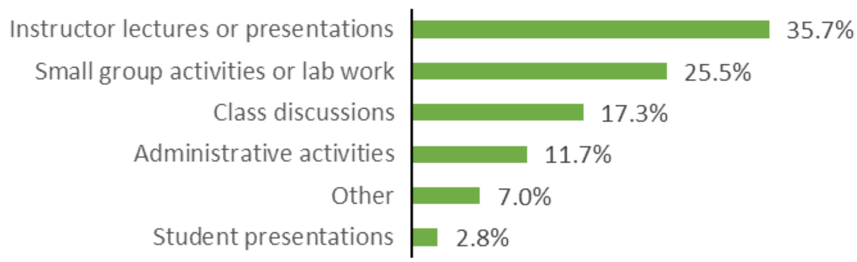

Figure 3. Time spent during class.

Survey respondents are generally familiar with using educational technologies (Figure 4). All of them were at least proficient with the learning management system (LMS), and 88.5% were also proficient with instructional technology. However, 38.5% were either not familiar or novice with using student-level data, and this difference in familiarity is significant based on the Chi-squared test ($\chi^2 = 30.429, p < .001$).

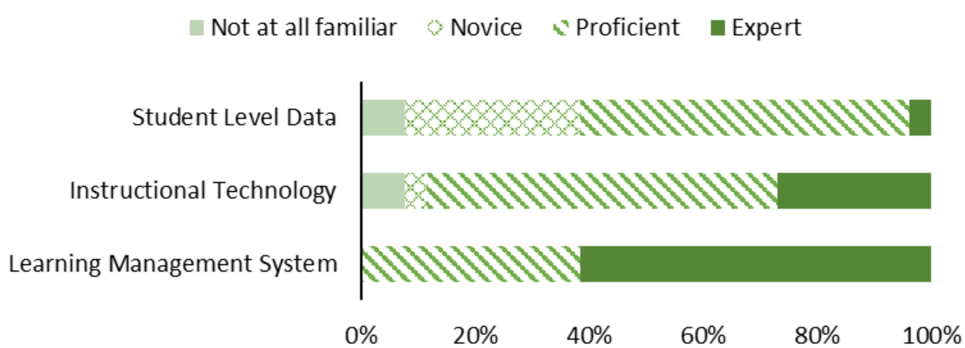

Figure 4. Respondents' familiarity with using technology and data in classes.

Most survey participants used Course Analytics monthly (54%), and weekly and semesterly use proportions were the same (23%) (Figure 5). The frequency of use may depend on the data types they are interested in. For example, 67% of semesterly users only looked at class-level data points, including data on the students' aggregated demographic and enrollment information, which are unlikely to change over the course of the semester. All weekly users utilized class- and student-level data (Figure 6). Noticeably, only two instructors (7.7%) reported sharing Course Analytics data with students; by contrast, 38.5% have discussed Course Analytics data with other instructors.

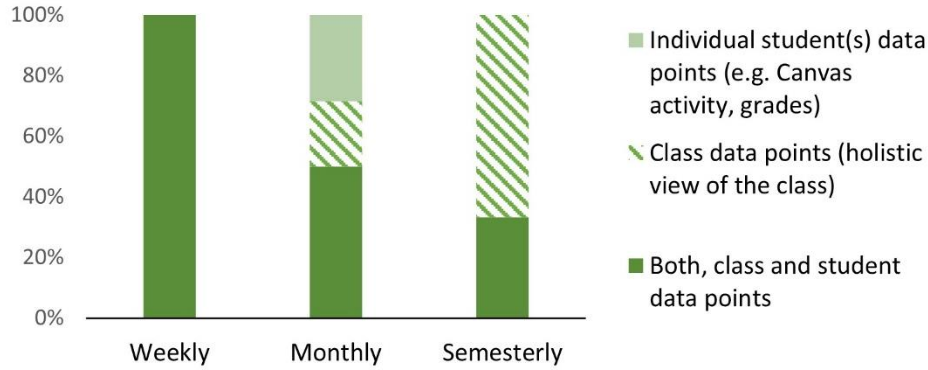

Figure 5. Respondents' use of different types of data in Course Analytics

Interview Results

We conducted 10 interviews (I1 – I10), averaging 48 minutes in length, and represent around 8% of the registered Course Analytics users. Most class sizes were less than fifty students and taught with multiple modalities. Instructors used a variety of instructional methods, including active learning opportunities. Half of the instructors (50%) indicated they used Course Analytics at the beginning of the semester, three instructors indicated a semi-regular weekly usage, and one instructor said "never".

Instructor Sensemaking with Data

Focused attention. Overall, instructors started using Course Analytics with the motivation to get to know their students better, in terms of students' backgrounds, enrollment, and academic standing. Wise and Jung (2019) consider this to be a form of interpreting data with a "focused attention" (p. 56). For example, many instructors reported using Course Analytics most at the beginning of the semester as they were interested in the class enrollment information.
For many instructors, the student demographics and background data could potentially help them offer support to students based on their needs and work towards a more responsive teaching practice. As one instructor said: "I use it a lot to understand what incoming students like where they're at, right? Semester standing, GPA, programs, stuff like that" (I4). Some student-level data, such as athletes or military designations, were not available, and instructors regarded them as potentially useful during the interview. However, as the data are presented in aggregation to protect student privacy and prevent intersectional identification, it also limits instructors' ability to make pedagogical changes for personalized support:

> It would be nice to know some of the identifiers that go with the students. So, I can go, okay, am I not doing a good job with certain groups that's falling behind? Right now, all I can see is their activity, and I don't know their name. (I1)

Striking the balance between protecting students' privacy and enabling personalized teaching is really important. One instructor shared: "some of these questions are awkward for an instructor to ask their students but we shouldn't have to ask as the [institution] already has most of this data

available" (S24). By using data analytical tools, instructors can learn about and know who their students are "in a way that is more private versus asking them to share openly" (S13).
The class size seemed to be an important factor that impacted instructors' use of data. One instructor with a class of less than fifty students said: "I know who everybody is, by the third week, but […] when you have, like 100 students or 200 students, it's harder to do that," without the data tool (I1). Similarly, "I have a large class this semester so I don't feel like I know the students as well as when I have a smaller class" (S28), implying that gathering data through technology is less useful for smaller classes. Smaller classes meant more time to know the background of all students because "you could get a lot from twenty students quickly" (I5) and how well they engage with the class through personal interactions and observations instead of analytic tools.

Beyond getting to know the students in their classes, instructors are motivated by other reasons to use the analytical tool. Several instructors were curious about a newly developed tool because they "think it's important to know what's going on at the university and what initiatives are happening" (I3). Two instructors described the tool as a "one-stop shop," as it decreases the amount of time spent piecing student data together from multiple databases: without it, "you pretty much have to spend hours downloading the roster and trying to like clean what should be easy information to obtain" (I5). Instructors saw the analytical tool as an efficient and time-saving process for seeing their class and student information.

Use context. When instructors approached the data with no focused attention or specific questions, it required more contextual information for instructors to make sense of the data. For example, one instructor shared that students' social identities are:

> not data that I take into consideration when designing my course, offering my course, etc. That being said, I had a student come up to me this semester, who said, I am an ESL [English as a Second Language] student, and 10 minutes on the quizzes is just not enough time. And I say, that is really helpful to know. Thank you for sharing that. [I] changed it to 15 minutes across the board. (I4)

The demographic data aggregated through analytical tools was not enough to inform this instructor's decisions; it was only through personal communication with students that he understood the implications of certain demographic identities. The classroom context can be combined with data to allow the instructor to fully express the situation. The instructor might not have known to ask a question about ESL students before going to the data; however, once informed of the issue, the instructor might review the number of other ESL students in the class. Survey results showed that most instructors consider themselves proficient at using student-level data, which is an important aspect of using analytical tools, so that the instructor might relate what they experience in class to the data displayed.

Students have no direct access to Course Analytics, yet some instructors use the tool to communicate better with students. One instructor showed aggregated "students' demographic, previous, [and] concurrent enrollment information during the first week, so they know that there could be peers taking the same class as them, etc. […] to spark some dialogue with their peers."

(S16). Another instructor showed students de-identified and aggregated data from previous semesters to help students map their potential outcomes based on prior students' performance. We did not interview students for this study, so it is unclear if seeing these attempts for connection was helpful or of interest to students. Sharing analytic data with students could be seen as a different form of whole-class scaffolding [33], in which these actions supported discussion and community.

Pedagogical Response

Instructors interpreted the data to understand the commonalities and differences among students, from which they could create student-level, subgroup, or class-level interventions. These data allowed instructors to know "how far in their programs my students are, what programs they're in […] what classes they're taken already, what classes they're taking concurrently" (I9) and "how many students were re-taking the class and that has led me to encourage finding study groups even more than I typically do" (I2). Several instructors said that after seeing the makeup of students' academic majors, they wanted to make their class interesting and relevant for students. Instructors might adapt and change lectures or the "delivery pace and content to some degree" (S13) to include materials of interest to students, which was important for classes open to different academic majors and student levels. As one natural science instructor said:

> if I see I have a lot of business majors in my class, I can talk more about the economics and the finance side of when you have natural disasters come through... I mean, I can talk about the physics of hurricanes and storm surge and all that, but why does any of that matter [to them]? (I7)

These instructional responses reflected speculation of students' skills based on their teaching experiences and understanding of students' academic progress, as illustrated here:

> [If I have] all third- and fourth-year students in the class I'm not going to worry about it […] If I've got, you know, a few second-year students in there, then it's questionable, and those students might not actually know how to find [writing genre]. So, I need to provide a resource or make sure that they're comfortable with that skill for the rest of the class already has it. (I5)

While some instructors did not report specific changes to their class design or teaching practices, they still appreciated the increased awareness of diverse student needs brought by the aggregated data. The available learning analytics "tempers […] expectations of what I expect" (I6) and helps instructors set the opportunities and challenges for their students. Notably, instructors did not lower their expectations for students' performance but rather used the data to prepare themselves for the class. One instructor shared quiz analytics with the students, showing them the distribution of scores, and used the data to "tell you if it's a good question or not" (I5), implying future consideration in the assessment. These changes in preparation reflect how instructors can use data to revise a course design.

Data also promoted instructor collaboration with each other when the co-enrollment information showed which courses most students took concurrently. Instructors were able to reschedule their assignments or tests and “schedule one makeup exam between us” (S2). By collaborating, instructors moved from “scrambling the week of the test” (I2) to proactively mitigating issues for students with overlapping exam schedules prior to an issue occurring. Another instructor said the data showed “a bunch of co-enrollments with another econ class and [used the data] to coordinate a midterm scheduled at the same time” with the other instructor (I2). By collaborating with colleagues in charge of the other course, instructors could prevent schedule conflicts or excessive student workload. These preemptive measures, when viewed from a program or system level, would likely help bolster student success by lowering institutionally created barriers and easing conflicting academic responsibilities on behalf of the students.

Obstacles Preventing the Use of Analytical Data

Experience and prior solutions. The Course Analytics application is relatively new, so instructors are still learning how to incorporate it into their teaching practice after previously developing their own practices and processes. Their existing practices and processes satisfy most of their needs, which means a decrease in the perception of usefulness of the Course Analytics tool. For example, the LMS already provides a gradebook, and “at a quick glance you could see in the gradebook late and missing, and they’re color coded in the gradebook, too” (I5). The advantage of using the tool is not obvious, so it is unsurprising that these instructors preferred to continue doing what works or is familiar. Similarly, some instructors prefer to use their own practices over the analytical tool because they can tailor the analysis to their needs.

> I already look at that data on my own. Like after every big assignment, I compute the average, I look where people are, and look at the distribution […and] I haven't found the information in [Course Analytics] to be that much more illuminating than Canvas and the anonymous survey I give to my class at the beginning of the semester (S9).

Instructors seemed to expect or need different information and were not necessarily using the application in the way it was designed to function.

Instructors’ use of the data may not be prioritized in their work. Some instructors have such a busy schedule that spending time with extra classroom data may not be a priority, as evidenced by their reported frequency of use of Course Analytics (Figure 5). Other instructors believed the data could be beneficial if explored more in-depth, as “a thing on my list to spend more time with” (I3). One instructor admitted to “only scratching the surface of what Course Analytics can tell me,” and understood it “could give me more information about [students] and I just have no idea” (I9). It was clear from the interviews that instructors would benefit from additional training in the Course Analytics application and usage scenarios. As the data used in learning analytics is only as good as the data entered, a reengineering of classroom activities might be needed to fully utilize the benefits of providing analytical data, though unlikely to occur.

Data accuracy. The process of data interpretation largely determines if and how instructors make pedagogical responses. However, some instructors expressed hesitations about trusting the data in the first place. Specifically, instructors' concerns focused on two aspects: Whether the data are accurate and synchronized in a timely fashion from data sources, and whether the metrics can be used as valid indicators of student engagement.

First, the implicit technical specifications in the data collection process, such as synchronization lag time, create concerns with the technology and discourage some instructors from using the data to inform teaching. Although Course Analytics synchronizes data every 24 hours and updates a timestamp on the bottom of the application's front page, "I'm supposed to use online activity data to inform decisions as an instructor, and that data isn't up to date, and it's not accurate" (I4). Similarly, the learning analytics data can appear inaccurate when there is any issue with data synchronization. For example, one learning tool acts as an in-class attendance or participation indicator. However, when the student failed to connect, "his scores haven't come over when the rest of the class's scores have come over," and now "his grade is a D." (I1). This failed synchronization means inaccurate grades, and can potentially be missed by instructors who teach large classes, or who are not as engaged with their students. Instances such as these, where instructors have lower trust, emphasize the importance of correctly and reliably represented data.

Second, activity collected online is a proxy for student engagement. The measurement of online activity only reflects students' behaviors trackable through the internet, which means it cannot provide insights to instructors who make little use of the LMS or other online learning applications. Even for instructors who are proficient with technologies, the fact that learning analytics does not capture *offline* activities can be problematic. Many instructors reported using lectures and small groups (Figure 3), and data are not currently collected for those activities, which renders these analytical tools ineffective for instructors to make a pedagogical response.

To what extent students' level of engagement can be measured through online activity is questionable in some instructors' opinions. If the tool comes without an explanation for the observed data, instructors need to make assumptions about data patterns. For example, when using the LMS for assignment submissions only, a student might "just type in the assignment really quickly and then get out," which means the time spent would be low and the instructor "didn't see that as a great effective way of sort of measuring performance" (I7). Or when an instructor has "an e-textbook [and] like a hard copy textbook, […] it might look like somebody's more engaged, and somebody is less engaged, but really like it's not that. […] it's hard to know what's actionable" (I2). Quantitative metrics may not fully or accurately reflect students' academic abilities or performance. Instead, these data must be coupled with what instructors experience in the classroom.

Across both survey responses and interviews, instructors found the static data, such as demographic and enrollment information, easy to interpret. However, their experience with dynamic data, such as cumulative online activity reporting, was less straightforward. Without proper contextualization of the definition and measurement of the "activity" process, instructors felt unsure of the metrics or what to do with the information.

Discussion

Pedagogical response to data analytics: maximizing the benefits

Static versus dynamic data. As more accountability is expected in STEM education, institutions are relying more and more on technology to help increase student success through data-informed decision-making [36]. The results of this study show that data-driven technology is not the panacea for the instructional or pedagogical response. The data features a key difference between static data and dynamic data that seems critical to the effective use of analytical tools. While not attended to in the Wise and Jung [33] "sense-making → pedagogical response" template, the difference in data types yields different degrees of interpretation and context.

Much like the "checkpoint" and "process analysis" [37], we found some data to be more helpful to instructors than others. Our results show that the static data, or background and demographic data that remains constant throughout the class, was more helpful and did not require frequent review. With this data, instructors made inferences about students' academic interests and resources from their existing knowledge. However, instructors reported difficulty interpreting the other data. Primarily, the dynamic data generated in real-time as students interact with online academic content is hard to understand. How these data are calculated and updated was unclear to the instructors, making them more complex to use. Sense-making is essential in knowing how to create a pedagogical response, so when instructors cannot make sense of the data or visuals, they may feel frustrated and confused with data applications [38].

This study demonstrates that static and dynamic data have different strengths and limitations for enhancing teaching practices and decision-making. The implication of the use of static without the dynamic data means any changes are short-term or temporary, made at the class level, and to meet the needs of those specific students during that semester; any long-term, course-level changes across semesters will require collaborative interpretation of analytical data. The instructors' use of static data was pedagogical in nature, even if limited to a single semester. For example, interviews revealed that understanding students' background information helps instructors work towards more inclusive teaching by incorporating different teaching resources to meet diverse students' needs. Building case scenarios or vignettes might help instructors know how to use and combine static and dynamic data better into actionable interventions.

Instructor collaboration. Extensive research documents how learning analytics can help instructors communicate with students and facilitate a collaborative learning environment [39], [40]. Our findings show that providing aggregated data can contribute to instructors' collaboration. Specifically, the aggregated data of students' enrollment history enabled instructors to initiate conversations about curriculum planning and development with each other. In the short term, such conversations help instructors avoid schedule and workload conflicts between different classes. In the long term, instructors can better understand how their teaching could better prepare students for sequential classes and overall learning outcomes.

The potential for collaborative efforts underscores the benefits of fostering a data-driven culture to promote the incorporation of learning analytics into teaching practices throughout an institution. As Greller and Drachsler [41] note, maximizing the benefits of educational data demands a collaborative effort from all stakeholders, including teachers. Instructor collaboration relies on the premise that enough instructors are using the tool to enable a shared understanding of how data can inform a better curriculum design.

Instructor collaboration might be an area to extend the Wise and Jung [33] template for sense-making → pedagogical response. By enhancing instructors' awareness and engagement with data-driven technologies, institutions can create an environment conducive to integrating data into pedagogical decisions. Instructors can help identify innovative ways to harness data, choose variables, and promote student-centered success from a singular class to across the curriculum. Institutions interested in developing collaborative efforts with analytical tools can do so with a conscientious approach to student data protection, privacy, and institutional policies. In this way, further iterations between taking action and checking for impact create a culture around data-informed and data-supported changes.

Ineffective utilization of data: addressing the limitations

Tool design and development. Although research on the challenges associated with learning analytics and similar tools has a long-standing educational focus [42], the lack of instructor and student involvement likely contributes to insufficient knowledge of these techniques [43], [44]. While clear and accurate data visualizations are critical for instructors' effective use of the data, instructors also need more guidance to interpret data and implement pedagogical changes.

This study identified the importance of contextualizing the student information. Presenting great visualizations might not be sufficient, as transparency in data collection, analysis, and reporting could be the key to instructors' trust in analytical tools [45]. For example, participants perceived Course Analytics data as inaccurate because data sources and synchronization processes are unknown. To prevent confusion and misconceptions from instructors, research could strengthen the design while user experience (UX) theories could enhance the status visibility and user learnability [46], [47].

By themselves, educational technologies often fail to account for the complexity of learning and the variety of student experiences [43] and do not provide insights into underlying causes and motivations [48]. We found these limitations were mostly associated with dynamic data, such as online activity. The sense-making process starts with a question from which answers are derived with the data; however, instructors were unsure of what question they had when looking at the dynamic data. As participants in this study reported, online activities are unlikely to represent students' full engagement or involvement with the course. Even if these data are fully representative, instructors might not know why certain patterns of activity or behavior show up or how to address issues. For example, a student with extensive online activity and a low grade is likely struggling with the content but trying. An instructor would need to reach out and ask the student about their work and contextualize the learning opportunities and activities to the student's efforts to know how best to support the student. Relying solely on learning analytics can lead to an incomplete or distorted understanding of a student's progress. Data-driven solutions accentuate how the tools should be treated like developing a hypothesis; instructors must incorporate the analytical data, the potential behavior and expected outcome, and other information known about the student before forming a complete evaluation about the student. To create the hypothesis, instructors need to identify the problem and then match to existing understandings of the situation and only then can sense-making occur. When an instructor approaches the aggregated data without a question or hypothesis, then their ability to gain information from the tool is restricted, and certainly no action can take place.

Technology integration and deployment. Successful integration and deployment of educational technology involves concerted efforts from multiple dimensions [29], [41] and requires appropriate instructor training. Consistent with other studies [49] instructors in our study did not spend a lot of time working with learning analytics. Findings from this study demonstrate the importance of increasing instructor and institutional buy-in during the process and the need for training. Notably, training will need to accommodate instructors with different levels of digital literacy and teaching philosophies and provide timely updates that keep instructors engaged with the fast development of data-driven technologies. Our results show instructors enjoy and want to collaborate with other instructors on their class schedules and mitigate student issues before they arise. Institutions interested in using the analytical tools should consider facilitating those interactions through sponsored workshops, executive support, or case-based examples.

Determining reasonable pedagogical actions based on analytical data can be challenging for instructors. Instructors in this study reported uncertainty about how to use students' learning data to improve their teaching or struggled to translate data into actionable insights. They expressed concern when the data were not representative of what the instructor experienced in class, which resonated with the findings of Case Study 1. In part, using a data-driven tool requires a thoughtful learning design and recognizing how and what data goes into the application [37], potentially leading to a course redesign. However, instructors may not be inclined to change their classes only to support learning analytics [50]. Several instructors in this study described how they developed their practices and processes and used them to form a pedagogical response. These instructors recognized a problem and sought an intervention that helped them answer the already formed question in the context of what they expected, using their experience and observations. Institutions interested in building useful and responsive data-driven applications might consider what data is most important to instructors and incorporate those specifics into the models.

Notably, research is limited in providing guidance on effective learning analytics training for instructors [45]. Regardless of discipline or pedagogical choice, instructors in this study had a difficult time describing how they know they're effective at teaching, which is very difficult to then translate into data visualizations. Reflecting on or checking for impact is an important part of the sense-making process for the pedagogical response frame. Training those stresses, coordinated collaboration, and connection, either by discipline or instructional method, would likely help instructors understand and use the data better. Instructors can have heavy teaching loads, research activities, and administrative responsibilities [41], making time constraints a barrier to learning and using the technology. As such, institutions will have to support and offer training programs for faculty to maximize their use of analytical tools, making connections between data points and goals, and incentivize excellence in teaching.

Overall Discussion

The findings of the two case studies converge on the dual challenges and opportunities of utilizing learning analytics to enhance educational practices in STEM. Study 1 highlights the limitations in capturing the multidimensional construct of student engagement, emphasizing the need for contextualized and nuanced approaches. Study 2 complements this perspective by exploring instructors' experiences with learning analytics tools, highlighting the difficulties in interpreting and applying analytics data effectively within pedagogical frameworks.

The connection between student engagement and instructor sense-making is central to the broader utility of learning analytics in education. Study 1 shows that observable online activity offers a limited explanation for changes in student engagement. This perspective aligns with findings from Study 2, where instructors reported difficulties contextualizing dynamic data such as clickstream interactions or forum participation. As educators often lack access to the rich, contextual data needed to interpret such metrics [51], the limitations identified in both studies point to a critical need for integrating learning analytics insights with qualitative and contextual artifacts. This integration holds particular relevance for STEM education, where learning often involves iterative problem-solving, collaborative inquiry, and lab-based experimentation. As suggested by Siemens [52], learning analytics' greatest potential lies in its ability to scaffold sense-making processes, enabling educators to align their teaching with evidence-based insights. For instance, STEM instructors could combine learning analytics outputs, such as patterns of student submissions, with reflections on classroom interactions to design timely interventions for at-risk students or adjust instructional strategies in real time.

Study 2 highlights the potential of aggregated learning analytics data to facilitate instructor collaboration, a finding supported by research on professional learning communities [53]. For STEM educators, collaboration informed by learning analytics can lead to more aligned curricula, improved assessment practices, and greater consistency in addressing learning objectives. However, barriers such as limited tool deployment and privacy concerns impede such collaborative efforts. Addressing these barriers through institutional policies and transparent data-sharing practices could help realize the full potential of learning analytics for STEM curriculum design. Both studies emphasize the importance of professional development to enable effective use of learning analytics, aligning with the literature for targeted training in data literacy and analytics interpretation [54]. STEM educators, in particular, may benefit from professional development that bridges their disciplinary expertise with pedagogical applications of analytics. Such training could focus on linking learning analytics insights to instructional design principles, enabling educators to use data to support active learning approaches, such as flipped classrooms or problem-based learning.

Limitations and Future Work

Both studies were conducted within specific contexts, limiting the generalizability of their findings. Study 1 examined a single course, with student behaviors tied to a unique set of online activities and contextual factors, such as course design and environmental influences. Similarly, Study 2 was limited by the size and characteristics of the instructor sample, which may not represent broader teaching practices across diverse disciplines or institutional settings. As a result, the findings of both studies may not extend seamlessly to other courses, disciplines, or institutions with different demographics or operational constraints. Study 2 focused solely on instructor-level usage of learning analytics tools, leaving institutional policies, collaborative practices, and student perspectives unexplored. Furthermore, all participating instructors voluntarily opted into the study, potentially biasing the findings toward those with an existing interest in educational technologies. This interest may not reflect the perspectives or challenges faced by instructors who are less inclined to adopt such tools, and thus limits the applicability of findings to wider faculty populations.

Future studies should explore learning analytics implementations across diverse courses, disciplines, and institutions to identify patterns and variations in their effectiveness. Comparative studies can help uncover context-specific factors that influence both student engagement and instructor use of analytics tools, offering insights into how learning analytics might be tailored to suit different learning environments. Future research should also include larger and more diverse samples of instructors, incorporating a range of disciplines, experience levels, and attitudes toward technology. Additionally, the role of institutional policies in shaping the adoption and ethical use of analytics tools should be studied. Exploring how learning analytics supports collaboration across departments, such as curriculum alignment and shared instructional goals, could also inform broader implementation strategies.

Lastly, advancements in generative AI offer transformative possibilities for addressing the limitations identified in both studies. Generative AI has the potential to process large volumes of data and provide explanatory analytic [55]. These capabilities could alleviate cognitive overload for STEM instructors by offering actionable recommendations based on learning analytics insights. For example, AI-driven tools might identify students struggling with foundational concepts in calculus and suggest targeted resources or alternative explanations, enabling instructors to intervene effectively. However, as argued by Holmes et al., [56], the integration of AI in education raises ethical considerations, particularly regarding data privacy and algorithmic bias. Future research should explore transparent design practices and ongoing dialogue between educators, technologists, and policymakers for integrating AI in learning analytics.

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