Student-facing Learning Analytics Dashboard: Profiles of Student Use

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***Abstract*—Student-facing learning analytics dashboards (LADs) provide visualizations of course-related information to help students understand and personalize their educational practices. As such, they can be viewed as a meta-cognitive tool that enables awareness, self-reflection and sensemaking of academic performance. While student-facing LADs are becoming a standard feature in educational software, questions have been raised about students' willingness to adopt LADs and their ability to interpret feedback provided by student-facing LADs. The extent to which student-facing LADs can broadly improve educational outcomes depends, in part, on students' ability to readily incorporate LAD usage in their educational workflows.**

This study investigates the use of a student-facing LAD, My Learning Analytics (MyLA), over the span of one semester in a university introductory science course. MyLA draws data from the campus learning management system (Canvas) and displays three visualizations designed to provide students with actionable information. Adoption and use of MyLA was voluntary. As an exploratory study of MyLA's use in an introductory science course, this work addresses three research questions: i) What are the characteristics of students that use MyLA?, ii) How do students make use of MyLA in their coursework?, and iii) What patterns of use are exhibited by more frequent MyLA users? The results indicate that given the opportunity to use a student-facing LAD, 33% of students made repeated use of the tool. Demographic data (e.g., gender, domestic/international student) did not predict MyLA usage but significant differences in mean cumulative GPA were found between non-MyLA users and MyLA users. Broad patterns of MyLA use were aligned with major assessments in the course (e.g., MyLA was used more often around exam dates) and the grade distribution view was the most commonly accessed. Among the most highly active MyLA users, two distinct profiles were identified: aware and sensemakers. Aware users made use of the dashboard on more than 12 distinct days across the course, primarily around exam dates, and stated that they accessed the dashboard to compare their performance with others. Sensemakers made frequent use of all three MyLA views multiple times over the semester to monitor their own progress, compare their grades to others, and check what materials other students had viewed.

LADs such as MyLA allow students to leverage what they already know about course assessment in their interpretation of the data presented, easing adoption and deployment of a student-facing LAD in higher education. As MyLA does not require that students have any additional training to interpret the visualizations they provide, LADs can readily be employed by students in introductory computing and engineering courses to provide them with feedback to help them plan for, monitor, and evaluate their academic progress.

***Index Terms*—learning analytics dashboard; student-facing learning analytics dashboard; self-regulated learning; course level micro-learning analytics**

I. Introduction

Analytics refers to a process of discovery and communication of informative patterns in data. In other words, analytics is used to make sense out of data. Put in context, the information discovered from the analysis and presentation of data can be used to inform decision making and advance progress towards particular aims. The modern educational environment often contains components that generate rich streams of data, such as learning management systems, online instructional videos and intelligent tutoring systems [1]. When properly analyzed and presented, these streams of learner data have the potential to aid learners in reaching their educational goals.

A learning analytics dashboard (LAD) is a display that "aggregates different indicators about learner(s), learning process(es) and/or learning context(s) into one or multiple visualizations" [2]. LADs present visualizations of relevant information pertinent to a goal, so it can be examined at a glance [3], [4]. By providing LADs directly to educators and learners, they can be part of a continual improvement process that leverages human judgement over automated decision making [5], [6]. LADs equip educators and learners to make informed decisions about learning or the learning environment and therefore, learning analytics dashboards can be viewed as an application of learning analytics. Early work applying data visualization and business intelligence in education was directed towards institutional or administrative processes (e.g., admissions, enrollment) [7]. Since then learning analytics dashboards have been designed to support educators and learners directly [8]–[10] or indirectly, enhancing retention or persistence [11], [12].

More recently, student-facing learning dashboards have emerged in which visualizations of performance are directly available to students [3]. Student-facing dashboards can be seen as a meta-cognitive tool that enables awareness, self-reflection and sensemaking of a student's learning to improve academic performance [5], [13]. Self-regulated learning involves active monitoring of several processes such as setting goals, monitoring progress towards those goals and responding to feedback [14]. Concerns have been raised about students' ability to interpret and act upon the data presented to them via LADs or students' emotive response to the feedback provided [15]–[17]. Concomitant with students' ability to correctly interpret and act on information from the dashboard is their actual use of the dashboard. It has been noted that the successful introduction of educational technology, such as student-facing LADs, requires planning and integration with intervention design [15].

This study aims to characterize university students' use of a student-facing LAD, called My Learning Analytics (MyLA), in one class over the course of a semester. Its contribution is to describe who chooses to use MyLA and how they make use of it in a natural setting. Specifically, this paper addresses the question of if you simply build a learning analytics dashboard and make it available to students for their coursework, will they make use of it? If so, which students use the dashboard and how do they use the dashboard?

II. Background

A. Student-facing LADs

At a broad level, student-facing LADs can be viewed as an application of personal informatics [18]. Such applications improve a user's self-knowledge through collection, review and analysis of an individual's past actions. Verbert et al. [5] described a four-stage learning analytic process model which includes awareness, reflection, sensemaking and impact. The data presented to students through a LAD can raise awareness of one's progress towards a learning goal. This awareness can prompt questions that through processes of reflection and sensemaking may lead to changes in behavior or new knowledge. These changes may impact progress towards a goal and thus a purposeful feedback loop is created.

Awareness of progress toward a learning goal can be readily elicited through use of a student-facing LAD. It has been noted that the primary goal of dashboards has been awareness [16]. It is less clear if students are willing and able to appropriately reflect and make sense of the information they are provided. Students' ability with regard to sensemaking will depend to an extent on the type of information provided. If the feedback is specific to a particular pedagogical intervention then students may not possess an adequate context to properly interpret the data. In other words, the student needs "an understanding of the pedagogical context in which the data was generated, knowledge of what particular analytics are meant to indicate, and an appreciation of how these relate to the learning goals of the situation" [19].

Another important aspect of sensemaking for a student-facing LAD is a frame of reference such as comparison with peers, progress towards goals or comparison with one's prior performance [15], [16], [20]. Peer comparison is a common frame of reference for performance in LADs but the effects of this frame of reference remains unclear [16]. Corrin and de Barba [21] reported that for most students, being compared to the class average was motivating but that it did distract some students from performance oriented goals. Tan et al. [22] found that high achieving students were further motivated through peer comparisons, pushing them to further engage while students towards the bottom of the class felt stressed. Wise et al. [15] noted that peer comparisons were found to be interesting, motivating and useful to many students but that they were stressful for some students below the class average.

Beyond the question of students' ability to make sense of a student-facing LAD is a more basic question of if students will even make use of it. It has been noted that simply availing users to a new educational technology does not mean that it will be adopted, regardless of its utility [19], [23]. If learning analytics are to make an impact on student learning, learning analytics-based applications need to be designed in such a way that they will impact broader patterns of educators and students. In this period in which many institutions are struggling with the increased demands of large class sizes and cost constraints [24], it would be ideal if learning analytics leveraged existing workflows and did not require large scale adoption or effort on the part of the instructors.

B. Course alignment and micro-level learning analytics

Applications of learning analytics can be characterized by the granularity of data collected and the target audience. At higher levels, data is collected with the aim of improving organizational efficiencies, such as advising [12], [25], student retention [26], and course sequencing [27], [28]. This level is sometimes referred to as the macro- or meso-level [19], [29]. At the micro-level, the focus is on providing teachers and learners with data that can be used for more immediate decision making in a learning event [15], [30]. Data reported to users at this level may be specific to a learning platform [31], provide personalized feedback [17], or be presented in a way that is agnostic to a specific learning intervention.

A course is considered to be well-aligned if course activities and course assessments support the course objectives. In a well-aligned course, the course objectives, activities and assessment are structured such that the course activities enable students to meet the course objectives and the course assessments are valid and reliable reflection of a student's progress towards meeting the course objectives [32]. Proper course alignment is considered a best practice and maximizes learning [32], [33]. Aside from being a practice that itself improves student outcomes, course alignment can improve student achievement through course agnostic micro-level learning analytics. If course activities and course assessments are well aligned to course outcomes, then a student's level of engagement with course materials or performance on course assessments is indicative of a student's attainment of the course objectives. This is not a subtle point and indeed it is how overall course evaluation should function (i.e., a student's final grade should indicate the extent to which he or she met the course's learning objectives). If a LAD enables a student to monitor her engagement with course materials and track progress on course assessments with the goal of increasing the percentage of points earned on assessments, then such an increase shown in the context of a well-aligned course suggests that the student has also increased attainment of the learning objectives.

C. *My Learning Analytics*

The LAD used in this study is called My Learning Analytics (MyLA). This system draws data from the campus learning management system (Canvas). My Learning Analytics was designed to provide actionable information that supports self-regulated learning and employs best practices from information visualization design to reduce students' cognitive load [34]. MyLA supports aspects of self-regulated learning by providing three distinct views to the students. The Files Accessed view, shown in Figure 1, shows commonly accessed course resources listed with bars indicating the percentage of students in the course that have accessed the resource. The bars are color-coded to indicate which resources the student has or has not accessed. The reported resource activity can be filtered by date (e.g., weeks 3 through 5 in the course) and reference group (i.e., show resources accessed by students with an indicated grade percentage). The Files Accessed view helps students monitor their progress to stay caught up with what other students are doing. The Assignment Planning view, shown in Figure 2, lists upcoming assignments by due date as well as the overall contribution to the overall grade for each assignment. Across the top of this view, a progress bar showing the status of each assessment is shown along with their relative weights and completion status. The Assignment Planning view aids students in planning their effort for upcoming assignments and monitor overall progress towards their goals for the course. The Grade Distribution view, shown in Figure 3, depicts the distribution of the overall grades of students in the course along with the course average and number of students. A student's relative standing in the course is indicated and labeled in the overall distribution. The Grade Distribution view aids students by monitoring their standing in the course and how it evolves over time. To encourage a mastery as opposed to a performance goal orientation [35], percentages of points are displayed in MyLA instead of letter grades. MyLA was developed iteratively, drawing on expertise from a diverse development team and piloted in late 2018 before its deployment for this study [34].

D. *Research Aims and Questions*

This study examined the use of a student-facing LAD in an introductory science course and was motivated by the following research questions:

- RQ1. What are the characteristics of students that use MyLA?
- RQ2. How do students make use of MyLA in their coursework?
- RQ3. What patterns of use are exhibited by more frequent MyLA users?

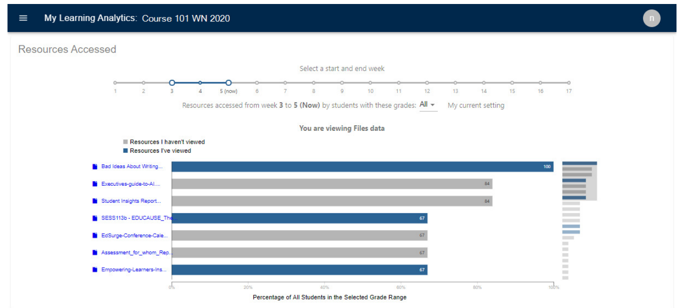

Fig. 1. The Files Accessed view lists the course's electronic resources available in the course management system. The length and color of the bar indicates the percentage of the class that has accessed the resource and if the student user has accessed the resources, respectively.

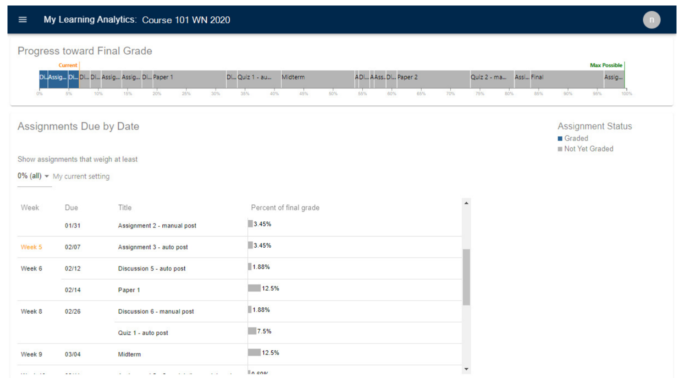

Fig. 2. The Assignment Planning view lists upcoming assignments and the contribution of each assignment to a student's overall grade.

III. Materials and Methods

A. *Participants*

The participants in this study were 253 students (170 male, 83 female) enrolled in an introductory climate science course at a large public research university in the United States during the spring 2019 term. This course was an elective course that fulfilled a science requirement for non-science majors. The composition of the course by academic level was 50, 60, 67, and 76 students which were freshman, sophomore, junior and senior, respectively. There were 232 domestic students and 21 international students. Midway through the term, the dashboard was made available on the course website. Use of the dashboard was voluntary and students were informed that their use of the dashboard would not be available to the course instructor. 138 students logged at least one interaction with the dashboard, and 158 students (users and non-users) completed the end of term survey.

B. *Procedure*

A recorded video that demonstrated the dashboard was made available on the course website when the dashboard was enabled for the course. The demo showed MyLA's three views and highlighted the specific features that students could control (e.g., select the comparison group for the Files Accessed

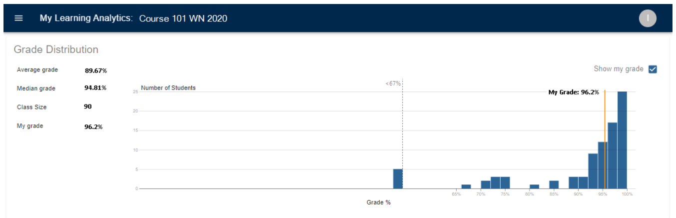

Fig. 3. The Grade Distribution view shows the distribution of the overall grade of students in the course.

view). Access to the dashboard was disabled after the term ended. Students' interactions with the dashboard were logged and students were asked to complete a survey about their dashboard use at the end of the term.

C. Data Analysis

As the focus of this work was on broader access patterns, the principal unit of time was access dates. For analyses presented here all logged user events were represented by a date and view type. This builds off of prior work that investigated access patterns within a particular MyLA session [34].

Students in the course were placed into three categories based on their overall usage of MyLA. Students that accessed MyLA on fewer than two distinct dates were labeled non-MyLA users(n = 172). These were users that either did not make use of MyLA or used MyLA in a very limited fashion (e.g., only tried MyLA when it was introduced to the course). Users that accessed MyLA on three or more distinct dates were labeled MyLA users (n = 72). Users that exhibited a high number of distinct dates of logged activity were labeled high-level MyLA users (n = 9). High-level MyLA users were defined as those with more than 2 standard deviations above the mean of distinct access dates for a student.

IV. Results

A. RQ1: What are the characteristics of students that use MyLA?

Of the 253 students in the course, 81 students were users (72) or high-level users (9) of MyLA, logging events on at least three different dates. The ratio of female to male students across the three usage levels is close to the overall composition of the course, at roughly 1:2 as shown in Table I. Representation of international and domestic students and academic levels across the three MyLA usage categories also closely mirrored the overall composition of the course, shown in Tables II and III.

To further characterize MyLA users, the mean cumulative grade point averages (GPA, based on a 4 point scale) of students were compared across usage levels. The mean GPAs by usage levels were 3.15 for non-MyLA users, 3.46 for MyLA users, and 3.7 for high-level MyLA users. A Kruskal–Wallis H test indicated a significant difference between mean GPAs at the $p < .01$ level, ($H=28.77$, $p < .01$). Follow-up pairwise Mann–Whitney tests with Bonferroni correction indicated that the differences in means between two of the usage groups, non-MyLA user vs. MyLA user, and non-MyLA user vs. high-level MyLA user, were significant at the $p < .01$ level.

B. RQ2: How do students make use of MyLA in their coursework?

Broad patterns of MyLA usage align with major assessment events in the course. Figure 4 illustrates the dates on which individual students logged events in MyLA. The first burst of activity occurred before the spring recess and includes the activity of those students who tried MyLA during the demonstration period. There are two additional clusters of activity corresponding to the dates for exams administered on March 15th and April 17th.

When considering day access counts irrespective of specific MyLA view, there were 620 distinct day accesses logged by students, calculated as the number of days a user accessed MyLA summed over all students. By grouping the distinct access days by student, a raw per student metric of MyLA usage was generated. Figure 5 illustrates the number of students per number of distinct access days and further characterizes the usage of non-MyLA, MyLA and high-level MyLA users. Separate distinct day counts of access were also calculated for each view and as seen in Table IV, the most popular view was the grade distribution view.

Students' preference to use MyLA to compare their overall performance to their peers was also noted in the survey results. One of the prompts in the survey was "please tell us

TABLE I
Distribution of Gender for MyLA Users by Usage

	Gender		
Usage	Female	Male	Total
Non-MyLA user	56	116	172
MyLA user	25	47	72
High-level MyLA user	2	7	9
Total	83	170	

TABLE II
Distribution of Academic Level for MyLA Users by Usage

	Academic Level				
Usage	Fr	So	Jr	Sr	Total
Non-MyLA user	34	41	50	47	172
MyLA user	16	15	15	26	72
High-level MyLA user	0	4	2	3	9
Total	50	60	67	76	

TABLE III
Distribution of Domestic and International Students by MyLA Usage Level

Usage	Domestic	International	Total
Non-MyLA user	157	15	172
MyLA user	67	5	72
High-level MyLA user	8	1	9
Total	232	21	253

TABLE IV
DISTINCT ACCESS DAY COUNTS BY MYLA VIEW

View	Number of Distinct Access Days
Assignment Planning	154
Grade Distribution	513
Files Accessed	134

why you typically used the Dashboard in this course". There were 54 MyLA and high-level MyLA users that responded to this prompt. Upon inspecting these responses, 33 mentioned comparing their grade or performance to that of their peers (e.g., "I would look at the grade distribution to see where I was at relative to other students in this course"). There were 12 students that made explicit mention of using MyLA to see what resources other students had accessed (e.g., "I used the Files Accessed section, in which I observed which files were mostly accessed as a study resource for the exam"). There were 10 students that mentioned checking their grade but without reference to peer comparisons (e.g., "To check my overall grade and to see the weights of each.").

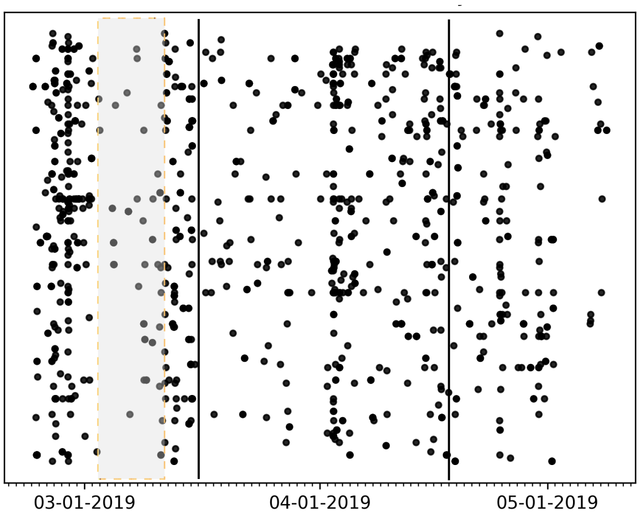

Fig. 4. Composite of MyLA access timelines for all students that logged events. Also indicated is the spring recess, shaded in grey, and solid vertical lines on March 15th and April 17th represent the dates of two exams.

To determine the regularity at which students accessed MyLA throughout the semester, the mean time in days between distinct dates of MyLA access was calculated. The resulting means are shown in Figure 6 and broken down by academic level and MyLA usage level. This figure indicates that many students, on average, were accessing MyLA regularly, with many mean times in the range of 5 to 10 days.

C. RQ3: What patterns of use are exhibited by frequent MyLA users?

As a group, the nine students who were high-level MyLA users showed a clear preference towards the Grade Distribution view. Specifically, their access days totalled 133 for Grade

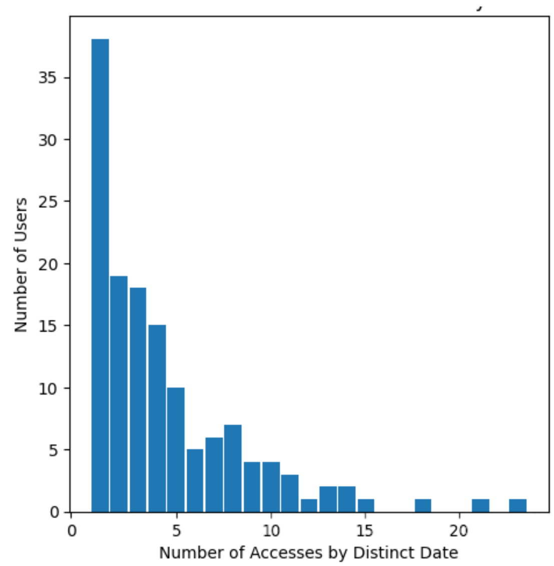

Fig. 5. Distribution of the number of users having a given number of distinct access days.

Distribution views, 25 for the Assignment Planning view and 18 for the Files Accessed view. An access timeline for the high-level MyLA users is shown in Figure 7. Pseudonyms were assigned to the MyLA users to protect their identities.

To better understand how these high-level users made use of MyLA, the event log for each user was probed. Six students had a clear preference for the Grade Distribution view. Mike, a senior, made extensive use of the Grade Distribution view, accessing it on 21 distinct days. On five different days, Mike accessed the Grade Distribution view more than once during the day. Mike did not log any events with the other two MyLA views. Similarly, Jonathan, a senior, used the Grade Distribution view on 20 distinct days. Jonathan accessed the Grade Distribution view multiple times on seven different days. Early on April 15th, Jonathan logged three Files Accessed views but his use of MyLA was largely the Grade Distribution view (38 of 45 logged events). Joe, a sophomore, accessed the Grade Distribution view on 15 distinct days. Joe accessed the Grade Distribution view five times throughout the day on April 3rd and of his 21 logged MyLA events, all but two were of the Grade Distribution view. Similarly, Steve, a junior, accessed the Grade Distribution view on 18 distinct days with multiple visits throughout the day on four of those dates. Mark, a sophomore, and Molly, a senior, also exhibited a preference for the Grade Distribution view, with both students accessing it on 12 distinct days but without repeat multiple visits on the same day.

Three of the high-level MyLA users interspersed their use of the Grade Distribution view with other views. Jan, a sophomore, made regular use of all three views in a single day on four different occasions. In total she accessed Files Accessed view on 6 different days, the Assignment Planner view on 8 days and the Grade Distribution view on 12 days. Frank, a sophomore, accessed the Assignment Planning view

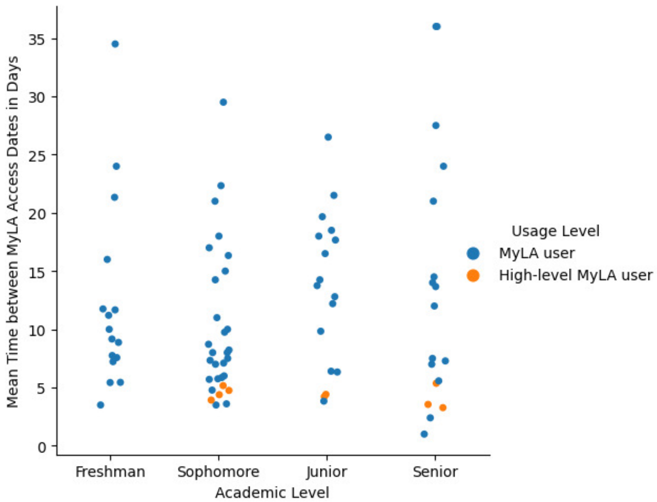

Fig. 6. The mean time in days between distinct access dates of students across all views.

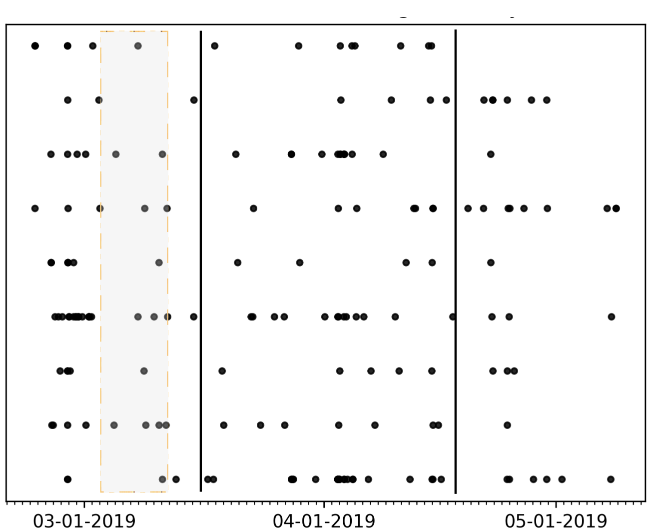

Fig. 7. Composite of MyLA access timelines for the Grade Distribution view of high-level MyLA user. Also indicated is the Spring Recess, shaded in grey, and the dates of two mid-term exams on March 15th and April 17th.

on six different days throughout the semester. Harry, a junior, accessed multiple views on three different days. As shown in Table V, all three users regularly used MyLA's functionality over a two month period.

D. Characterization of MyLA users

As described above, MyLA users were categorized into three usage categories (i.e., non-MyLA user, MyLA user, and high-level MyLA user) based on their level of interaction with MyLA. After analyses of the usage patterns of students in each of these three interaction levels, user categorization was further refined into four categories to account for not only level of interaction with MyLA but also distinctive patterns of use. In doing so, MyLA users were characterized as Browsers and high-level MyLA users were split into two separate groups,

TABLE V

Dates Activity along with View Type: Assignment Planning (AP), Grade Distribution (GD), Files Accessed (FA)

Jan	Harry	Frank
2/22 - AP, GD, FA	2/24 - AP, GD	2/24 - AP, GD
2/26 - AP, GD	2/26 - GD	2/26 - AP, GD
3/2 - GD	3/1 - GD	2/27 - AP, GD
3/7 - GD	3/4 - GD, FA	3/10 - GD
3/11 - AP, GD, FA	3/8 - GD	3/13 - AP
3/17 - GD	3/10 - GD	3/20 - GD
3/25 - AP	3/11 - GD	3/28 - GD
3/28 - AP, GD, FA	3/15 - FA	4/1 - AP
4/3 - AP, GD, FA	3/19 - GD	4/7 - AP
4/4 - AP, GD	3/23 - GD	4/11 - GD
4/5 - AP, GD	3/26 - GD	4/15 - GD
4/10 - GD, FA	4/2 - GD	4/22 - GD
4/11 - FA	4/7 - GD	
4/14 - GD	4/15 - AP, GD, FA	

Aware users and Sensemakers. These four categories further characterize MyLA users and were created to further explore student use of the MyLA dashboard across all three research questions. These categories are defined as non-MyLA users, Browsers, Aware users and Sensemakers and described as follows: The non-MyLA users were defined as students who never logged into the system or did so less than three times over the semester. This group contained 68% of all students with both genders proportionately represented as well as all academic levels. The average GPA for this group, 3.15, was significantly lower than the means of all other groups.

Students identified as Browsers were occasional users of the system, between three logins and two standard deviations above average. The 28.5% of students in this group also were proportionally represented by gender, academic level, and domestic vs. international students with an average GPA of 3.46, which was statistically similar to the high-level user groups (Aware and Sensemakers, GPA of 3.7). These students logged into the dashboard over a wide range of dates during the course (See Figure 6), primarily to view grade distribution, although other views were also accessed.

Aware users made up 2.4% (6) of the students in the class and there were no freshmen within the group. They are high-level users of the MyLA dashboard who visited the dashboard more than 12 distinct days across the semester. Often their visits occurred before the midterm exams and primarily focused on the Grade Distribution view of the dashboard (See Figure 7). In their survey responses, the aware users stated that they accessed the dashboard to compare performance with other students.

The Sensemaker group contained 1.2% of the students (3) in the course and both female and male students. These high-level users of the MyLA system accessed the dashboard multiple times over the semester in patterns that were distinctly different than the other high level-user group. The members of this group often followed this pattern when accessing the dashboard: Activities (to monitor their own progress), Grade Distribution (where they could compare their grades to others), and then Files Accessed (view course materials that they and others had viewed). This pattern repeated multiple times before each midterm exam (see Figure 7 and Table 5). These students stated that they used the dashboard to access grade distribution, but also "to watch lectures" and "see who looked at what files".

V. Discussion

A. If you build it, will they come?

One concern with introducing a new application in a user's established workflow is whether it will be accepted and used [36]. The argument is that by simply availing students to a new educational tool does not mean that they will use it or know how to use it properly. With MyLA, many students did make use of the dashboard. A demonstration of MyLA was presented to the students in the course, but beyond posting the video and the instructor announcing that the tool was turned on, students were neither verbally encouraged nor offered an incentive (e.g., extra credit) to use MyLA yet students did and did so a number of times throughout the semester. The students' repeated MyLA activity over the course of the semester is indicative that some students did find value in the tool. Had students been reminded of the availability of MyLA, the usage level would have likely been much higher. Most of the non-users who responded to the survey said that they did not make use of MyLA because they had forgotten that it was available.

The voluntary adoption of MyLA by many students may be due in part to it being intervention agnostic. That is, MyLA is a micro-level LAD and it is not tied to specific educational tools, tutoring systems, interventions, or pedagogies. It references course constructs (e.g., grade, artifacts accessed, upcoming assessment items) that are commonly used and well understood by students. The usage patterns of MyLA (e.g., repeated use, tool being used extensively around major assessment events) are congruent with the interpretation that students understand what information MyLA provides and how it relates to course assessment.

B. Balance between potential reach of a student-facing LAD and the feedback it provides

An advantage of an intervention agnostic, student-facing LAD such as MyLA is its positioning for broad use with little effort required by the instructor. As noted, educational tools are part of a larger teaching and learning process, and their successful adoption requires thought and intentionality on the part of the user to incorporate a new educational tool into their processes [15]. Additionally, if the LADs are providing intervention specific feedback then students may not have the pedagogical knowledge necessary to act upon it. MyLA does not require intervention specific pedagogical knowledge nor does it require students to change their existing practices. Students are accustomed to monitoring their progress in a course through their performance on assessment items. They are also accustomed to discussing course resources and upcoming assessment items with their peers. Thus, there is a trade-off between the likely reach of a tool and the level of detail in the feedback it provides. LADs that reference common course artifacts may not provide specific feedback but they can be deployed without relying on instructors' involvement. Reducing the reliance on instructor involvement with the LAD in turn increases the reach of the LAD since its deployment is not dependent on the instructors' adoption.

C. Awareness and sensemaking with MyLA

Although researchers have asserted that student-facing analytic dashboards can facilitate peer comparison [8] and aid self-regulated learning [12], how this affects students has not been clearly defined. Research has noted that students with grades below class average found the peer comparisons stressful [25], [29]. With the non-MyLA users' grade average significantly lower than all other groups of users, we posit that prior peer comparisons, even without the use of a dashboard, could have contributed to the lack of use by these students. Adding a customization where students can choose to hide comparisons could offer students a less stressful environment which utilizes the affordances of a student-facing dashboard without peer comparisons. In fact, in response to student feedback, we made it possible for students to hide their position in the overall grade distribution. In addition, the higher grade averages for students in the other MyLA user groups, as well as their overall greater focus on the grade distribution view, aligns with prior research by Tan et al. [22] who found peer comparison to be motivating for higher achieving students.

One of the more ambitious goals of student-facing LADs is to support students as they develop awareness of progress towards a learning goal. Through this study, two patterns of behavior in the highest-level user group were identified that show evidence of this progress. First, the Aware group (n=6) focused almost entirely on the grade distribution view of the dashboard, sometimes checking their grade vs. others within the class multiple times a day. Through the survey responses, the Aware users were accessing this view to compare their progress to others' standing multiple times before each midterm, as well as after. With awareness one factor shown to be improved through the use of a student-facing dashboard, this use of peer comparison illustrates student use of the resource for this purpose. This awareness is the first aspect of sensemaking necessary to reflect and make sense of their behaviors, potentially leading to improved self-regulated learning [12]. The Sensemakers (n=3) pattern of use for the MyLA dashboard was more complex. They fluctuated between grade distribution, assignment planning, and resources accessed throughout the course, especially before the midterms. By interleaving views of the grade distribution among their views of assignment and resource reviews, this subgroup of high level users appear to use the dashboard for sensemaking purposes. The users' survey responses also support this finding, with students stating that they utilize the dashboard for more than simple peer comparison. Through this use of the dashboard as a meta-cognitive tool [9], these students made sense of their own behavior and performance, and adapted through use of resources to improve their understanding before each testing opportunity. These actions indicate that the users were moving toward the ultimate goal of dashboards: supporting self-regulated learning [8]. By including instruction for students about the potential for improved learning and sensemaking when using multiple views of the dashboard, students could better understand how they learn and lead to increased levels of self-regulated learning. More research is needed on how students use multiple views of the dashboard to move towards this goal.

D. Limitations and future directions for research

Limitations to this study include the amount of student feedback and logged activity. The student survey administered in this study included only 2 or 3 open-ended questions which limited the amount of specific qualitative feedback collected. Student responses were short and typically confirmed activities that were already captured by the event log (e.g., if a student noted that they used MyLA to check their grade, this was already evidenced by repeated visits to the grade distribution view). Broader usage patterns (e.g., distinct access dates) were chosen to accurately characterize user activity. For the high-level MyLA users identified in this study, most had only one or two logged events for the day. Following the growing trend of using trace data to capture self-regulation [37], future directions of study could focus on more fine grained analyses of the different usage patterns. Triangulating this with more qualitative data, such as a think-aloud protocol, could be utilized to better understand a student's use of MyLA and how students make sense of the data provided by MyLA. For example, by combining methods the usage patterns exhibited by high level users (e.g., the exclusive use of the grade distribution view by Aware users; concurrent use of multiple views by the Sensemakers) could be probed further to determine students' goals and the extent to which students are making sense of the data provided through MyLA. Instrumenting pop-up questions directly into the MyLA interface would be another method to investigate students' motivation and intention, and perhaps capture students' thinking as they engage in MyLA use. For non-MyLA users, particularly those that tried MyLA but did not use it for more than one or two days, it is of interest to know why they choose not to use MyLA. Was their lack of usage because they did not find value in the tool or simply because they forgot it was available? In future implementations of this dashboard, reminding students that it exists and doing so throughout the semester, especially before exams or other high stakes assessments, may increase the number of student users.

VI. Conclusion

This study addressed a basic question of LAD adoption: if you make a learning analytics dashboard available to students for their coursework, will they make use of it and if so, how? In the context of an introductory university science course, many students made repeated use of MyLA, with some high-level usage students exhibiting patterns of use consistent with awareness or sensemaking. As a LAD that is not tied to particular learning intervention but rather references common course constructs, MyLA does not require that students have pedagogical knowledge to interpret the visualizations provided. Furthermore, students' familiarity with the course constructs referenced by MyLA's visualizations may lessen the barrier for adoption of student-facing LADs. In this study, over a third of students in the course chose to make use of MyLA. Future research on MyLA and other dashboards should address how to make them most useful to students and how to best convey their value to all students regardless of their academic standing.

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