Blackboard
ANALYTICS™

Blackboard Data Science Research Brief

Student interest & patterns in learning analytics notifications

John Whitmer, Ed.D.
Director of Analytics & Research
Blackboard, Inc.

Daniel Nasiatka
Blackboard, Inc.

Timothy Harfield, Ph.D.
Blackboard, Inc.

There is a small amount of empirical research about how students respond to learning analytics notifications. In this study, we analyzed clickstream data from student activity in the Ultra experience of Blackboard Learn with 22,227 notifications sent to 3,679 students in Spring 2017. Students opened notifications at relatively high rates overall (37%). They demonstrated a clear preference for notifications that compared them to peers in their course compared to notifications about trends in their own activity over time. Students were clustered into five groups based on the frequency of notifications received; these clusters indicate that student behavior within the LMS is highly consistent over the duration of a course. The findings in open rates were consistent across the student clusters, showing that both low-performing and high performing students have interest in this type of information.

Introduction

Providing students with information about how they are performing in a course, and alerting them in advance if they are at risk of not passing a course, has been suggested as a powerful way that learning analytics can be used to improve educational outcomes (Dahlstrom, Brooks & Bichsel, 2014). Student-facing dashboards are being increasingly built into educational technology applications, providing direct interventions to the people who need them most and can immediately act upon them. However, there is little empirical research in this area, and the research that has been conducted has been conducted with relatively small numbers of students and has reported mixed results (Aguilar, 2016; Teasley, 2017).

One concern raised in prior research was whether all students would benefit from the same message and type of analytic feature, or whether these features should be differentiated based on student background characteristics and performance within a course. In the Ultra experience of Blackboard Learn, we created a feature that sends students (as well as faculty) notifications about individual trends in performance and performance relative to peers, using rule-based thresholds to identify high and low performers.

Prior to releasing this feature, we conducted user research that found students from low GPA backgrounds valued this information more than students from high GPA backgrounds (Teasley & Whitmer, 2017). This research was conducted through interviews and surveys of students in a simulation of the feature, asking them to reflect on their experience in prior classes. While useful and important, we now have data from real instructional contexts and can augment these initial findings with authentic student behavior.

The following questions oriented this study:

1. Do students consistently receive the same notifications? Can the notifications be used to classify student performance?
2. Are students interested in notifications, as indicated by the rate at which they open them? Does this interest vary by the type of notification received?
3. Does interest in notifications vary by students classified by patterns of notifications received?

Context

Learning analytics notifications are a feature in the Ultra experience of Blackboard Learn. Any institution on the SaaS hosting platform that has enabled Ultra Base Navigation will automatically deliver rule-based notifications to students. Notifications are designed to encourage students to improve their performance, while also recognizing positive performance and LMS activity. These rules compare students to their behavior in the prior week (e.g. trends in their behavior) as well as to that of other students in the course. The specific notifications investigated in this study are provided in Table 1.

Notification	Rule
GradeIncreased	Grade increased 10% compared to prior week
GradeDropped	Grade dropped 10% compared to prior week
GradeInHighest	Grade in top 10% of students in course
GradeInLowest	Grade in bottom 5% of students in course

Table 1 - Notification rules

These notifications are included in the Learn "activity stream," a centralized interface that provides students and faculty with information about their courses: assignments due, other deadlines, etc. If a student clicks a notification, they are presented with a dashboard that shows more detailed information. This is usually a chart that plots their performance over time or illustrates their position relative to other students in the course. Finally, there is a follow-on action that a student is encouraged to take to address the notification. This pattern is held for all notifications in the course.

Screenshots illustrating this workflow are included in Figures 1 and 2. The messages used in the notifications are intentionally "light," using a "concerned friend" tone to keep students' interest while providing sometimes concerning information about the behavior or performance in a course. In addition, there are phrase variants used for some of the rules to provide novelty in the notifications and maintain student interest over the life of a course.

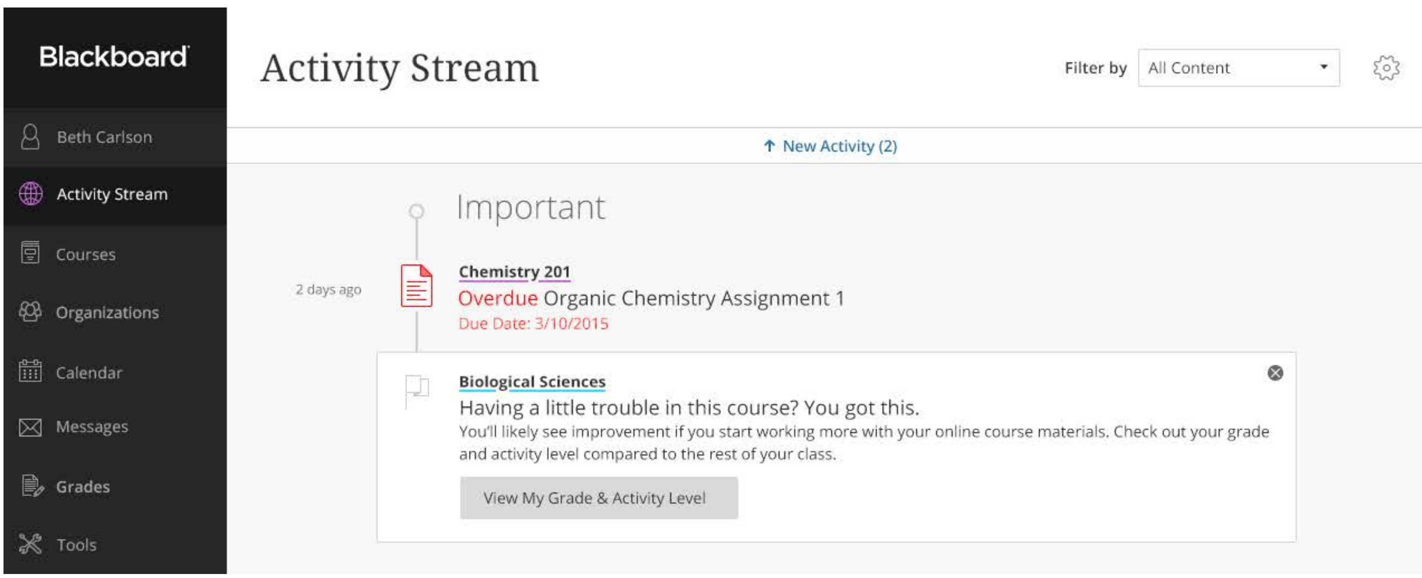

Figure 1 - Notification in Activity Stream & Visualization

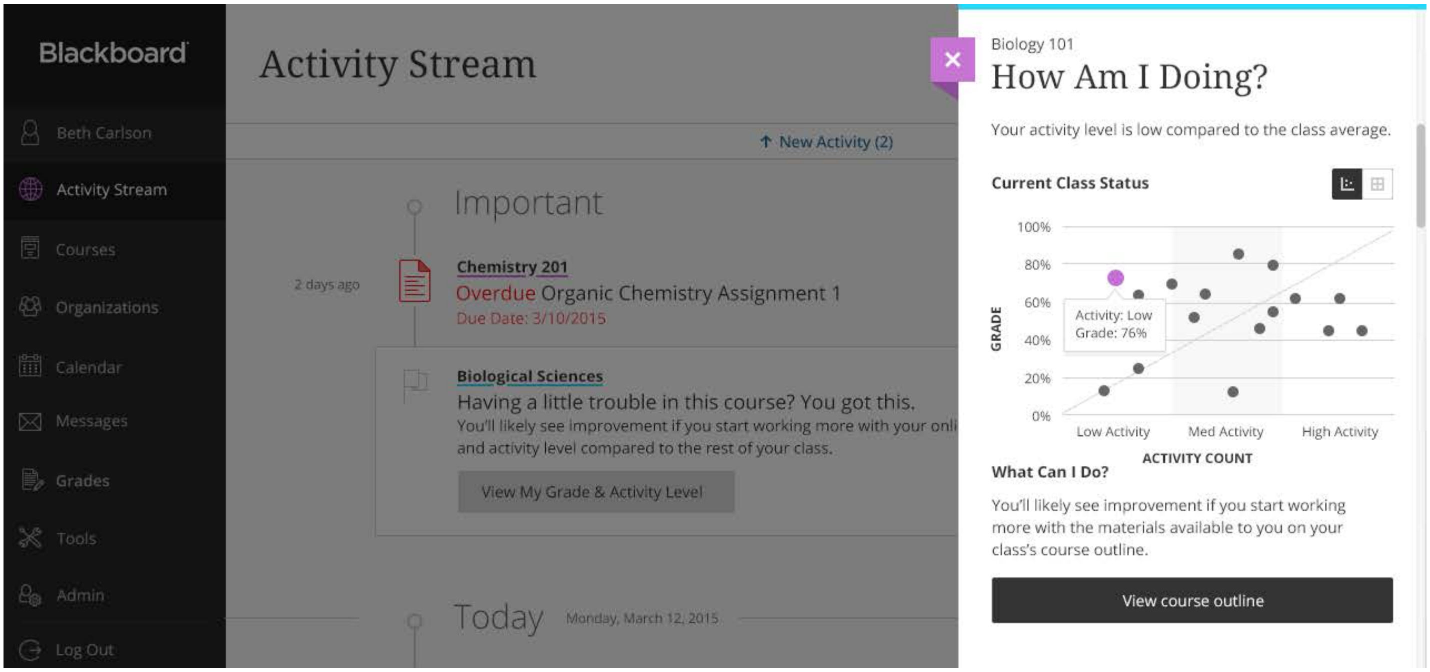

Figure 2 - Notification Visualization

Data Used

In this study, we used a sample of courses running in Learn SaaS that had Ultra Base Navigation enabled. We performed an archival investigation (no A/B testing) with data collected on notifications throughout the semester. We filtered data for institutions with a large number of notifications (n > 2,000), providing suitable variability in course types and students to create a generalizable sample for research purposes. The data set used was anonymized. No student, faculty, nor course-level descriptive information was included in the data set.

Measure	Count
Notifications	22,227
Students	3,679
Courses	414
Institutions	4
Notification types	4

Table 2 - Data analyzed

Notifications were included only if rendered to the student's device screen. Simply triggering the rule was not considered sufficient to be included as the student did not have an opportunity to open the notification. In addition, records were included only if students were found to have online activity several weeks after a notification to control for students that had dropped a course. The resultant data set is described in Table 2. There were 22,227 notifications observed by 3,679 students in 414 courses across four institutions. This is a substantially diverse data set to provide insights into student behavior with respect to notifications.

Methods

Several statistical methods were applied to the dataset to answer the research questions. First, students were grouped by patterns in the types of notifications received. For this analysis, we implemented the k-means cluster analysis. The number of notifications per type per student was aggregated, as the goal was to cluster students across all courses. The input to the algorithm was the normalized number of notifications received in each category. The algorithm partitions N data points into K disjoint subsets S_j containing N_j data points, minimizing the criterion until convergence occurs to stable sets of labels. Experimentally, we found 5 clearly identifiable groups in our data, which are labeled and discussed in detailed in the findings section.

$$J = \sum_{j=1}^{K} \sum_{n \in S_j} \left| \frac{x_n}{\sum x_n} - \mu_j \right|^2$$

Figure 3: K-Means clustering formula

To perform the statistical significance tests for the difference in notification open rates between groups, we implemented standard chi-square tests with Bonferroni adjusted p-values for multiple comparisons. The data was first aggregated to a granularity of notification type for an initial analysis; for a more detailed analysis, we aggregated the data to a granularity of student cluster and notification type. We considered all notifications rendered on student devices. If a student opened a notification multiple times, we only counted the first opening in our analysis.

Findings

Do students consistently receive the same notifications, or do these notifications vary during a course? Can the notifications be used to classify student performance?

The first item we investigated was the frequency with which students received the different types of notification. This was important as a first step in order to pursue the question of whether students with different academic performance levels have different responses to the notifications. Our prior research predicted that students with low performance were likely to open the notifications more frequently, however we wondered if students who consistently received high notifications were more active overall and would be more likely to open the notifications.

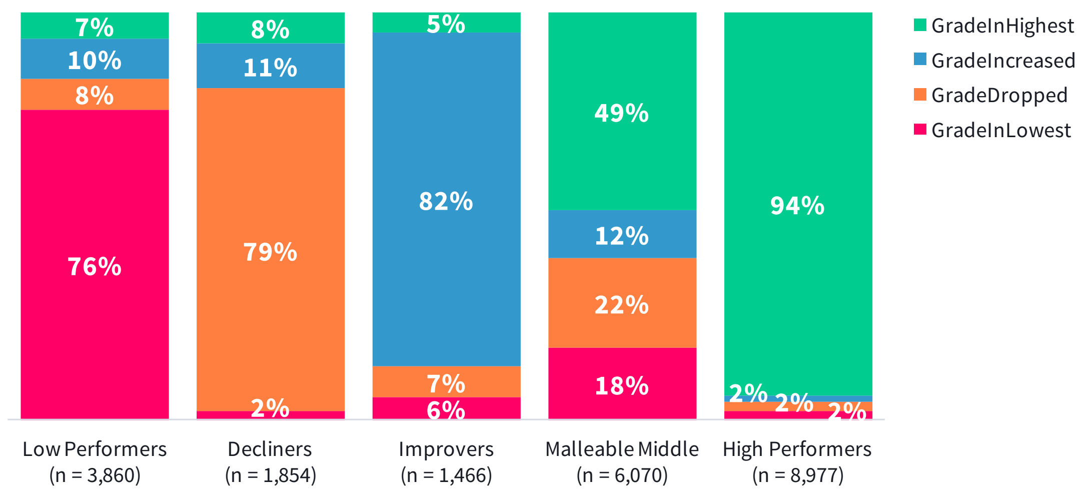

Figure 4 - Notification type distribution by student cluster

We found that there were five clearly distinct groups identified through K-Means cluster analysis. There is one cluster per notification type, with an additional type (the Malleable Middle) that receives a variety of notifications.

The count and distribution of cluster types are described in Figure 4 and Table 3, along with an explanation of each type.

Cluster	Count	%
High Performers	1,232	33%
Low Performers	623	17%
Improvers	419	11%
Decliners	555	15%
Malleable Middle	850	23%

Table 3 – Frequency of student clusters

1. **High Performers** received almost exclusively notifications that they had a high grade relative to other students in the course. Unlike other clusters, they received almost no other notification types. These students started with high grades and continued to earn those grades. The largest proportion of students were in this category, perhaps due to the 10% rule threshold.
2. **Low Performers** were in the opposite position of High Performers. They almost exclusively received notifications that they had a low grade relative to other students. They received more of other notification types than High Performers, but this was by far the most frequent notification that they received.
3. **Improvers** largely received notifications that their grade had increased. These are students whose grade increased throughout the term, but rarely to the extent necessary to place them in the top 10%of the class.
4. **Decliners** were in the opposite position as Improvers. Their grade started high but decreased frequently in the course. These students also received other notification types, but rarely received GradeInLowest. It is possible that these students started with a very high grade and declined yet still passed the course.
5. Students in the **Malleable Middle** show similar traits to High Performers, with over twice as many notifications in the GradeInHighest type compared to other types, but they also received a large number of GradesDropping and GradesInLowest notifications. These students had highly varied achievement during a course.

Given the differences between the number of students in each category, there may be some hesitation to see percent of notifications used for clustering. However, the above result was not sensitive to filtering for students receiving a high volume or low volume of notifications. These clusters were also consistent across institutions. In the following analysis, we examine how these groups interact differently with the LMS notifications that they received.

How interested are students in notifications, as indicated by the rate at which they open the notifications? Does this interest vary by the type of notification received?

Considered across all students, there were high open rates for these notifications, demonstrating a strong interest in this information. As illustrated in Figure 5, the open rates ranged from around 25% to over 40%. Data about open rates on other types of notifications (e.g. deadlines, new content) was not readily available, but based on prior experience and activity levels in the LMS we believe that these are high levels of activity that indicate students are interested in this type of information about their course performance.

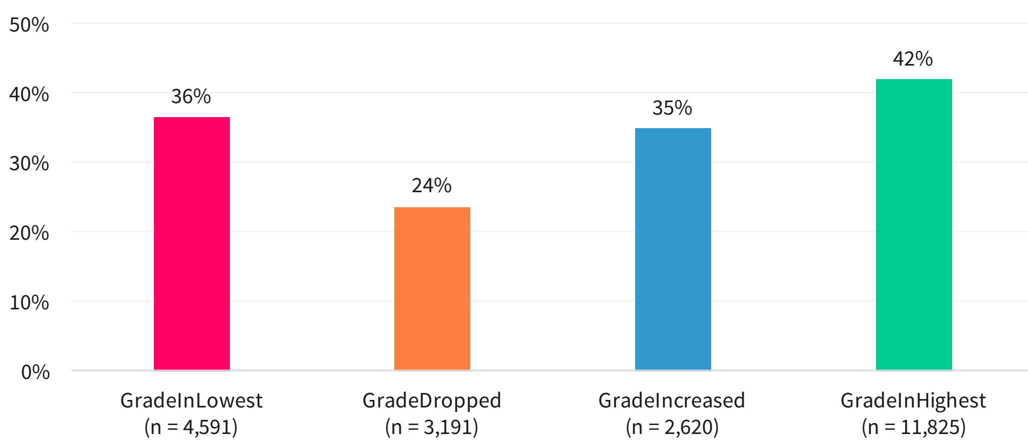

Figure 5 – Open rates by notification type (all students)

In Table 4, the results of significance testing are shown. There were statistically significant differences between open rates when considered as pairs, based on the type of notification in all but one case. Despite showing opposite performance information, GradeInHighest and GradeInLowest notifications were opened more frequently than GradeDropped and GradeIncreased ($p < 0.01$). The more frequently-opened notifications compare student performance to other students.

Notification Type 1	Notification Type 2	N1	N2	Open Rate 1	Open Rate 2	P-Value
GradeDropped	GradeInHighest	3191	11825	24%	42%	6.86E-83
GradeDropped	GradeInLowest	3191	4591	24%	36%	1.43E-33
GradeDropped	GradeIncreased	3191	2620	24%	35%	8.81E-21
GradeInHighest	GradeIncreased	11825	2620	42%	35%	2.60E-11
GradeInHighest	GradeInLowest	11825	4591	42%	36%	1.95E-10
GradeIncreased	GradeInLowest	2620	4591	35%	36%	0.176

Table 4 – Comparison between notification open rates

There are several possible explanations for why most students seem to prefer to view these notifications over the others. One reason could be that the dashboards for these comparative notifications convey information not otherwise available to students. Students can easily see whether their grades increased or decreased by viewing the gradebook, but their relative standing to peers could not otherwise be surfaced. It could also be that peer comparisons are an innately stronger psychological motivator than independent performance information. Whatever the underlying cause, this result validates that comparative performance information is valuable to students.

An additional result was that students prefer notifications with positive news (GradeInHighest and GradeIncreased) over notifications with negative feedback (GradeInLowest and GradeDropped). This is a counter-intuitive result counter to findings in our prior research study (Teasley & Whitmer, 2017). In that study students from high GPAs were more skeptical about the analytics results, although mostly about LMS activity information. From a product intent perspective, analytics notifications are intended largely to improve the performance of students at risk of failing a course. Understanding that high achievement is of stronger interest to students has implications for what types of messages and how this feature is designed. It also says that institutions and educational technology companies should be cognizant of all students when developing learning analytics notifications.

Does this interest vary by students classified by patterns of notifications received?

The clusters of students indicate that there were very different profiles of students in the study in terms of their academic performance within the courses. As indicated in Figure 4, there are substantial difference in overall open rates by cluster as well as the open rates by notification type within cluster. For a complete table of results, see Appendix 1.

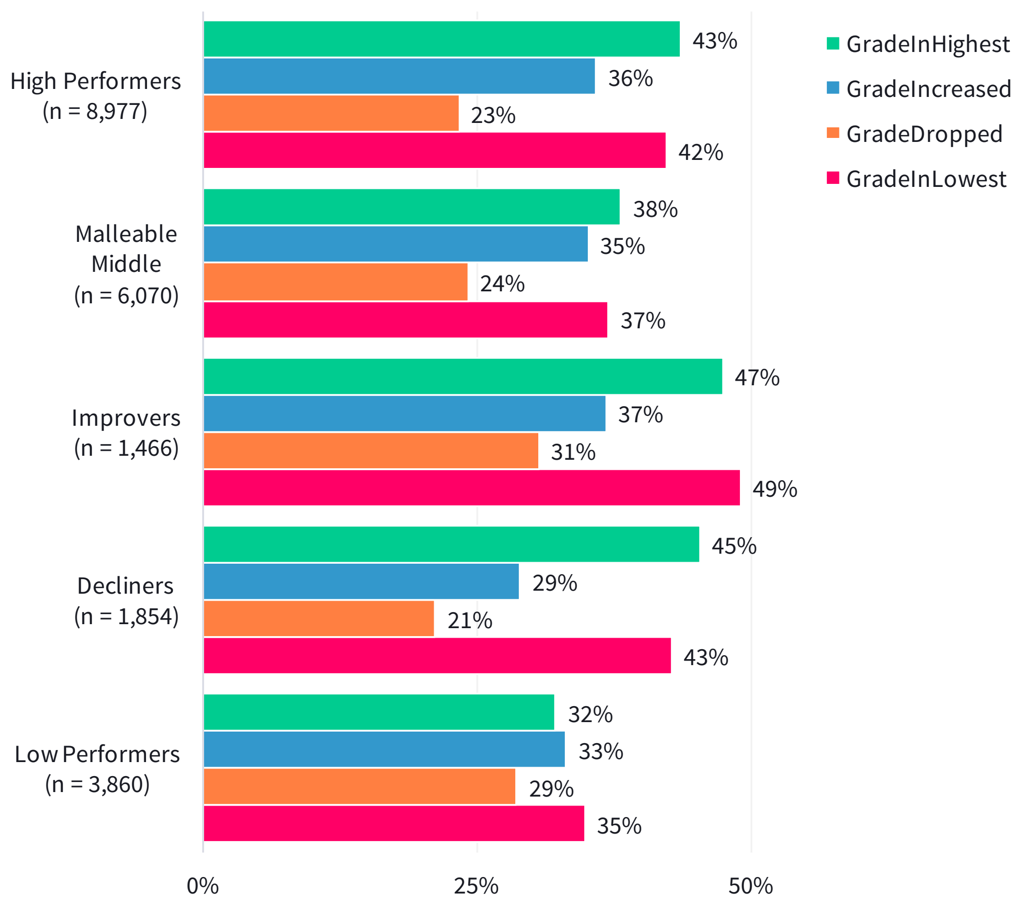

Figure 6 - Notification Open Rates by Cluster and Type

In several clusters, overall rates of opening notifications are different than others. Improvers showed the highest open rates for each type of notification, though for the GradeInHighest and GradeInLowest notification types, this was not statistically significantly different from their counterparts, the Decliners.

High Performers had the highest overall number of notifications opened ($p < 0.01$), as they receive almost all of their notifications in the GradeInHighest category. This result supports prior researching showing that learning outcomes are related to LMS activity and engagement. This is one reason why it is not sufficient to look at overall open rate differences, as the characteristics of students receiving these notifications vary widely.

Another finding was that the cluster of students receiving varied notifications (the Malleable Middle) tended to have lower interaction with the dashboards. Although these students most often received GradeInHighest notifications (similar to High Performers), their open rates were not significantly different from the Low Performers. This is a surprising result. It would seem that novel and diverse notifications would be of more interest to students than a steady stream of the same message, but that was not the result in practice. It appears that students found dashboards more interesting when receiving consistent feedback.

Significant differences were found within each cluster of students between the relative-ranking notifications (GradeInHighest and GradeInLowest) and the grade change notifications (Grade Increased and Grade Dropped) for all clusters except for Low Performers ($p < 0.01$). This finding mirrors what was discussed previously for the overall value of these types of notifications and those explanations apply equally in this analysis. However, it is notable that Low Performers did not show a significant difference in open rates between comparative information and self-information notifications. Furthermore, Low Performers showed significantly less interest in all notifications than other groups. This may indicate that these students have lower overall activity and interaction with the LMS than other groups. An alternative explanation is that these students are more sensitive to constructive information, as they almost exclusively received messages about low performance.

It is also interesting to note that none of the student clusters showed a statistically significant difference in open rates for positive/negative feedback for relative-ranking notifications (GradeInHighest vs GradeInLowest), while several groups did show a significant difference in open rates for positive/negative feedback for grade change notifications (GradeIncreased vs GradeDropped). That is, the results indicate that the students interested in comparative information are agnostic to whether the feedback is positive or negative, while students show a significant preference for positive feedback when presented with a notification focusing on the student's own performance. As the results from our prior study with the University of Michigan showed, this finding could identify an opportunity to better engage students by refining the messaging in the notifications. Alternatively, another explanation could be that students of all types are more sensitive to negative personal feedback than negative comparative feedback.

Limitations and Next Steps

This study investigates how students receive and interact with notifications; the ultimate question is whether this behavior has a noticeable impact on student grades or online activity. We attempted to investigate this question for this study but encountered confounding factors and unclear data that lead us to believe that an archival study at scale is not feasible. Students in this dataset often received multiple types of notifications from courses around the same time, so it was difficult to attribute any outcome to a single notification. In addition, there were large variations in course grades and activity between groups and over time. A better approach to exploring this relationship would be to conduct a small-scale study with a single course or group of courses; ideally using an experimental design or longitudinal analysis.

This study was also limited to investigation of grade-based notifications and a relatively small number of institutions which was constrained by the available data. Future research should expand into LMS behavior notifications and a larger number of institutions.

Conclusions

In this study, we contribute to the research literature and communities of practice interested in student-facing learning analytics notifications. The findings indicate that students have strong interest in this type of information to assist them with their academic endeavors. This research differs from prior work in that we use anonymized archival data collected from authentic courses that provides insights into actual student interactions and behavior with these notifications.

In most cases, students exhibited consistent trends in their grade achievements that resulted in them receiving the same notifications over time. The distribution is partially due to the thresholds used for the notifications in the study, but also indicates that student grade achievement and position relative to other students is largely consistent over time. Surprisingly, students still have a strong interest in the notifications that they receive, despite receiving a consistent message that is associated with their course position.

Students also demonstrated a clear preference for notifications comparing them relative to other students over notifications showing changes in their achievement over time. This is a key advantage of these type of notifications and learning analytics dashboards. Student responses confirm student interest in this type of feature. Further, students appear to be most interested in notifications that recognize positive achievement compared to those that identify areas for improvement, counter to the intent of most notifications, which is to identify at-risk students and help motivate changes in behavior. These approaches can co-exist, but this finding emphasizes the importance of keeping positive nudges in notifications that are developed.

References

Aguilar, S. (2016). Perceived motivational affordances: Capturing and measuring students' sense-making around visualizations of their academic achievement information. (Doctoral Dissertation) University of Michigan, Ann Arbor, MI.

Dahlstrom, E., Brooks, D.C., and Bichsel, J. (2014, September). The Current Ecosystem of Learning Management Systems in Higher Education: Student, Faculty, and IT Perspectives. *Research report.* Louisville, CO: ECAR. Available from https://net.educause.edu/ir/library/pdf/ers1414.pdf.

Teasley, S. D. & Whitmer, J. (2017). Surprising Lessons from Research on Student Feedback about Data Dashboards. Blog Post. Published February 2, 2017. URL: http://blog.blackboard.com/research-student-feedback-data-dashboards/

Teasley, S. D. (2017). Student Facing Dashboards: One Size Fits All? *Technology, Knowledge and Learning*. doi:10.1007/s10758-017-9314-3.

Appendix 1: Notification open rates by cluster

Cluster	Notification 1	Notification 2	n1	n2	rate1	rate2	P Value
High Performers	GradeDropped	GradeInHighest	245	8194	23%	43%	0.0000
High Performers	GradeDropped	GradeInLowest	245	320	23%	42%	0.0000
High Performers	GradeDropped	GradeIncreased	245	218	23%	36%	0.0040
High Performers	GradeIncreased	GradeInHighest	218	8194	36%	43%	0.0265
High Performers	GradeIncreased	GradeInLowest	218	320	36%	42%	0.1510
High Performers	GradeInHighest	GradeInLowest	8194	320	43%	42%	0.6875
Malleable Middle	GradeDropped	GradeInHighest	1141	2962	24%	38%	0.0000
Malleable Middle	GradeDropped	GradeInLowest	1141	1265	24%	37%	0.0000
Malleable Middle	GradeDropped	GradeIncreased	1141	702	24%	35%	0.0000
Malleable Middle	GradeIncreased	GradeInHighest	702	2962	35%	38%	0.1407
Malleable Middle	GradeIncreased	GradeInLowest	702	1265	35%	37%	0.4335
Malleable Middle	GradeInHighest	GradeInLowest	2962	1265	38%	37%	0.5103
Improvers	GradeDropped	GradeInLowest	180	141	31%	49%	0.0012
Improvers	GradeDropped	GradeInHighest	180	112	31%	47%	0.0043
Improvers	GradeIncreased	GradeInLowest	1033	141	37%	49%	0.0056
Improvers	GradeIncreased	GradeInHighest	1033	112	37%	47%	0.0311
Improvers	GradeDropped	GradeIncreased	180	1033	31%	37%	0.1293
Improvers	GradeInHighest	GradeInLowest	112	141	47%	49%	0.8016
Decliners	GradeDropped	GradeInHighest	1310	199	21%	45%	0.0000
Decliners	GradeDropped	GradeInLowest	1310	68	21%	43%	0.0001
Decliners	GradeIncreased	GradeInHighest	277	199	29%	45%	0.0003
Decliners	GradeDropped	GradeIncreased	1310	277	21%	29%	0.0070
Decliners	GradeIncreased	GradeInLowest	277	68	29%	43%	0.0408
Decliners	GradeInHighest	GradeInLowest	199	68	45%	43%	0.7780
Low Performers	GradeDropped	GradeInLowest	315	2797	29%	35%	0.0283
Low Performers	GradeDropped	GradeIncreased	315	390	29%	33%	0.2196
Low Performers	GradeInHighest	GradeInLowest	358	2797	32%	35%	0.3449
Low Performers	GradeDropped	GradeInHighest	315	358	29%	32%	0.3559
Low Performers	GradeIncreased	GradeInLowest	390	2797	33%	35%	0.5322
Low Performers	GradeIncreased	GradeInHighest	390	358	33%	32%	0.8150