Course Engagement Patterns

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Mathematics and Non-Mathematics Courses

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MICHIGAN VIRTUAL LEARNING®
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About Michigan Virtual Learning Research Institute

In 2012, the Governor and Michigan Legislature passed legislation requiring *Michigan Virtual*™, formally *Michigan Virtual University*®, to establish a research center for online learning and innovation. Known as *Michigan Virtual Learning Research Institute*® (*MVLRI*®), this center is a natural extension of the work of *Michigan Virtual*. Established in 1998, *Michigan Virtual's* mission is to advance K-12 digital learning and teaching through research, practice, and partnerships. Toward that end, the core strategies of *MVLRI* are:

- Research — Expand the K-12 online and blended learning knowledge base through high quality, high impact research;
- Policy — Inform local, state, and national public education policy strategies that reinforce and support online and blended learning opportunities for the K-12 community;
- Innovation — Experiment with new technologies and online learning models to foster expanded learning opportunities for K-12 students; and
- Networks — Develop human and web-based applications and infrastructures for sharing information and implementing K-12 online and blended learning best practices.

Michigan Virtual dedicates a small number of staff members to *MVLRI* projects as well as augments its capacity through a fellows program drawing from state and national experts in K-12 online learning from K-12 schooling, higher education, and private industry. These experts work alongside *Michigan Virtual* staff to provide research, evaluation, and development expertise and support.

About the Credit Recovery Series

MVLRI has launched a series of quantitative research reports exploring characteristics of students in state virtual school courses, specifically focused on those who took courses for credit recovery. This series was motivated by an attempt to accumulate empirical evidence related to student performance and learning engagement patterns to better understand learners in K-12 online learning environments. Using *Michigan Virtual School*® (*MVS*®*)* data, the first report in the series explores the enrollment and performance characteristics of students whose reason for enrolling in their course was credit recovery (CR). The next three in the series placed more fine-grained variables at the analytic center by examining students' engagement patterns in their courses. This study chose some of the subject areas most frequently taken by CR students and focused on two types of time series variables, including weekly attempted/earned scores from the gradebook data and weekly sums of minutes spent on the course from the learning management system (LMS) data. Using time series clustering methods, studies were to depict data-driven learner groups and the plausible interpretation of their behavioral patterns.

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Executive Summary

Two previous reports in this series were devoted to examining behavioral indicators and to suggesting thereby how students, including those whose enrollment reason was credit recovery (CR), engaged in the first part of the Algebra 2 course. Time series clustering methodology was applied to the two types of course-activity data, namely weekly data on both the students' attempted scores and the number of minutes spent in the LMS. The current report extended the work exploring learning profiles to other subject areas most frequently taken by CR students: Algebra 1, English Language & Literature 9, and U.S. History & Geography 1.

Clustering results were discussed as a way of providing data-driven benchmarks for the optimal course behavior patterns, which may be used by instructors and course mentors for guidance in monitoring progress. We selected a cluster that was more likely to result in positive course outcomes for both subject areas per semester. Their passing members' averages on the ratio of attempted scores to the full course points in percentage at the four time segments, and the totals of minutes spent in the learning management system (LMS) for the four time blocks are as follows:

Attempted scores in the fall semester:

- *Mathematics/Persistent engagement for the entire semester: Week 5 = 13%, Week 10 = 36%, Week 15 = 59%, Final week = 94%*
- *Non-mathematics/Persistent engagement for the entire semester: Week 5 = 14%, Week 10 = 30%, Week 15 = 54%, Final week = 91%*

Time-recorded in the LMS in the fall semester:

- *Mathematics/Final spike: Q1 = 386, Q2 = 271, Q3 = 227, Q4 = 750 in minutes*
- *Non-mathematics/Frequent small peaks: Q1 = 464, Q2 = 668, Q3 = 528, Q4 = 668 in minutes*

Attempted scores in the summer semester:

- *Mathematics/Slow start and then persistent engagement: Week 2 = 0%, Week 5 = 11%, Week 8 = 41%, Final week = 80%*
- *Non-mathematics/Persistent for the entire semester: Week 2 = 4%, Week 5 = 37%, Week 8 = 80%, Final week = 94%*

Time-recorded in the LMS in the summer semester:

- *Mathematics/Significant time investments from the beginning of the semester to the several weeks prior to the final: Week 2 = 454, Week 5 = 1,099, Week 8 = 467, Final week = 214 in minutes*
- *Non-mathematics/Persistent for the entire semester: Week 2 = 109, Week 5 = 433, Week 8 = 707, Final week = 1608 in minutes*

Introduction

From the first three studies in this credit recovery (CR) series, we learned that CR students tended to achieve lower levels of course outcomes than students whose reasons for enrollment were other than CR (Kwon, 2017a). Using weekly attempted scores as a behavioral indicator, CR students were clustered into the group with the majority of learners in the first part of the Algebra 2A course by completing assignments consistently throughout the semester. It has been found that summer semester data also captured more varied learning profiles, revealing that CR students' most likely profile was that of persistent coursework; however, some showed profiles that featured procrastination or no attempts to complete course activities and assignments at all (Kwon, 2017b).

When time investment in the course was examined, it was found that the majority of students were members of the group that made an intensive time investment during the final weeks, whereas a small portion of students were assigned to the group featuring multiple occurrences of intensive time investment over academic semesters of either 10 or 20 weeks. Some CR cases were found in the majority learner group, but they were also often assigned to variously profiled groups, including having no peaks in the final weeks, devoting significant time to the course at the beginning of the semester, and investing considerable time at either the beginning or the end of the semester. It has been found that most failing CR members showed time records that were well below their cluster averages during the short academic semester of summer semester. In contrast, the three CR members who passed were more likely to have invested a greater amount of time in the course than the cluster average for at least one quarter of the semester (Kwon, 2017c).

The last report of the CR series extended the previous work exploring learning profiles to other courses in order to relate data-driven learner groups to subject areas. Another study investigated the differences between subject-specific groups in K–12 online learning contexts: Oliver, Kellogg, and Patel (2010) surveyed students and teachers and found that student ratings for mathematics courses were more negative than for English and social studies courses. For example, on some survey items regarding perception of course success, student respondents from mathematics courses tended to perceive the online learning experience as being less successful, rich, and recommendable for other students. Analyzing qualitative responses, the study pointed out that it is important to ensure effective means for asking questions; receiving in-time support; having teachers' demonstration, modeling, and additional explanation; supplementing a lack of experience with online mathematics tools and prerequisite skills; and providing opportunities for collaboration. The authors also highlighted that putting forth a sufficient effort to study was critical, from the students' perspective.

With those findings in mind, the question has been raised as to what student efforts look like across different subject areas. To facilitate understanding of this topic, the last study in the CR series was devoted to an investigation into the learning profiles of course engagement for the entire enrollment case and the CR-focused case in both mathematics and non-mathematics courses. Among the courses most frequently taken by CR students, Algebra 1A, English Language & Literature 9A, and U.S. History & Geography 1A were selected. Data from the two non-mathematics courses were combined to ensure sufficient sample size. Because the previous studies indicated different patterns in students' engagement and time investment between the regular and summer semesters (Kwon, 2017b; Kwon, 2017c), data from the fall and summer were explored separately. This study design returned a total of 119 non-mathematics course enrollments, 23 of which failed (81% pass rate) and 14 (of the 119) were CR enrollments. There were 54 mathematics enrollments, 20 of which failed (63% pass rate). Of the 54 enrollments, only two were CR. For the 10-week summer semester, the final data contained a total of 72 non-mathematics enrollments, 20 of which failed (passing rate of 72%). Twenty-three of 72 were CR cases. The total of 94 mathematics enrollments included the failing case of eight (passing rate of 91%) and the CR case of 20.

Taken together, the present study centered on the time series variable, including weekly attempted scores and weekly total minutes spent in a learning management system (LMS). In clustering those time series variables, we pre-specified the number of clusters at five. Since the attempted score data for non-mathematics combined two sets of gradebook data for the courses of English Language & Literature 9A and U.S. History & Geography 1A, the raw data were transformed to the ratio of attempted scores to the total possible scores in percentage for the final time series data. Research questions that guided the study are as follows:

- When the weekly attempted scores from the gradebook data were used as a measure of inter-subject similarity, how were the clusters formed?
- When the weekly time spent in the LMS was used as a measure of inter-subject similarity, how were the clusters formed?
- How were clustering results different when comparing reasons for CR enrollment and course types, in a descriptive sense?

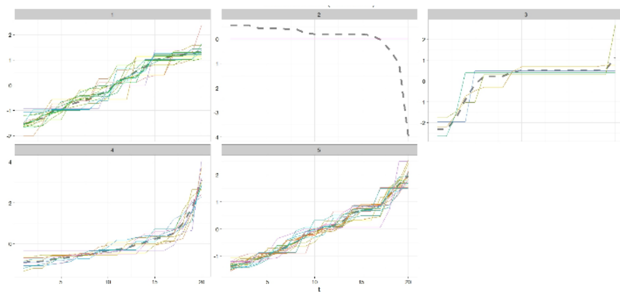
Results

Engagement Patterns in the Regular Semester

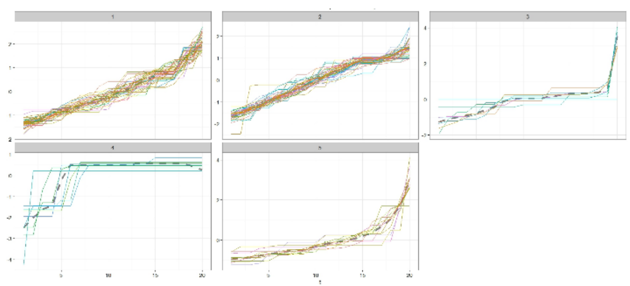
In order to explore engagement patterns for the regular semester, the fall semester was chosen because spring semester had a small sample size for both subject areas and because the trimester was based on a different time series. When the time series data from 54 mathematics enrollments (Algebra 1A) and 119 non-mathematics enrollments (English Language & Literature 9A and U.S. History & Geography 1A) were introduced, the five data-driven clusters indicated engagement patterns over the 20 weeks as shown in Figure 1. The bold dashed line represents prototypes of members' course engagement.

Figure 1. Time Series Plot of Cumulative Attempted Scores for Fall Semester

Mathematics



Non-Mathematics



The patterns of consistent and persistent coursework throughout the semester were found in cluster 5 in mathematics (Math5) and cluster 1 in non-mathematics (Non-math1), given their gradual increase from the bottom-left corner to the top-right corner. Another profile portrays that over most weeks, members' time investment increased and that rise was slowed in the final weeks, as shown by cluster 1 in mathematics (Math1) and by cluster 2 in non-mathematics (Non-math2). Early completers were presumably members of this type of cluster. The next representative profile shows less active engagement in most of the time period but then is followed by the final spike. This includes cluster 4 in mathematics (Math4) and cluster 3 in non-mathematics (Non-math3). The remaining clusters (i.e., Math2, Math3, and Non-math4) would indicate a de facto dropping out of the course.

Table 1 presents cluster compositions and a descriptive summary of attempted scores at the four time segments. The size refers to the percentage of cluster members out of the entire sample per subject area. Percentages pertaining to failing, CR, and passing CR cases are the ratio of members to respective total counts of failing, CR, and passing CR cases. Averages of final grades for individual clusters are also included in the summary table. Descriptive summary includes the average of attempted scores across cluster members at weeks 5, 10, 15, and 20. For both mathematics and non-mathematics, the total counts of enrollment records, failing cases, CR cases, and passed CR cases in the fall semester are reported. Total average is calculated from the entire sample of data at weeks 5, 10, 15, and 20.

Table 1. Cluster Summary of Attempted Scores for Fall Semester

Profile	Cluster	Size	Fail	CR	Pass CR	Avg. Gr.	W5[1]	W10	W15	W20
Persistent throughout semester	Math5	39%	25%	--	--	73	11	32	52	83
Persistent throughout semester	Non-math1	35%	13%	57%	56%	77	13	28	52	87
Persistent prior to final weeks	Math1	30%	45%	50%	--	55	12	28	55	63
Persistent prior to final weeks	Non-math2	40%	30%	29%	33%	79	21	46	71	86
Final spike	Math4	20%	--	50%	100%	84	5	14	27	94
Final spike	Non-math3	8%	17%	7%	--	54	6	17	21	62
Final spike	Non-math5	10%	--	7%	11%	84	6	15	28	92
De facto dropping out of course	Math2	4%	10%	--	--	0	0	0	0	0
De facto dropping out of course	Math3	7%	20%	--	--	16	11	17	17	21
De facto dropping out of course	Non-math4	8%	39%	--	--	4	3	5	5	5
Total Count	**Math**	**54**	**20**	**2**	**1**	**--**	**--**	**--**	**--**	**--**
Total Average	**Math**	**--**	**--**	**--**	**--**	**63**	**10**	**25**	**44**	**72**
Total Count	**Non-math**	**119**	**23**	**14**	**9**	**--**	**--**	**--**	**--**	**--**
Total Average	**Non-math**	**--**	**--**	**--**	**--**	**71**	**14**	**32**	**51**	**79**

Note 1: The data illustrating attempted scores is the ratio of attempted scores to the total possible scores for each course in percentage.

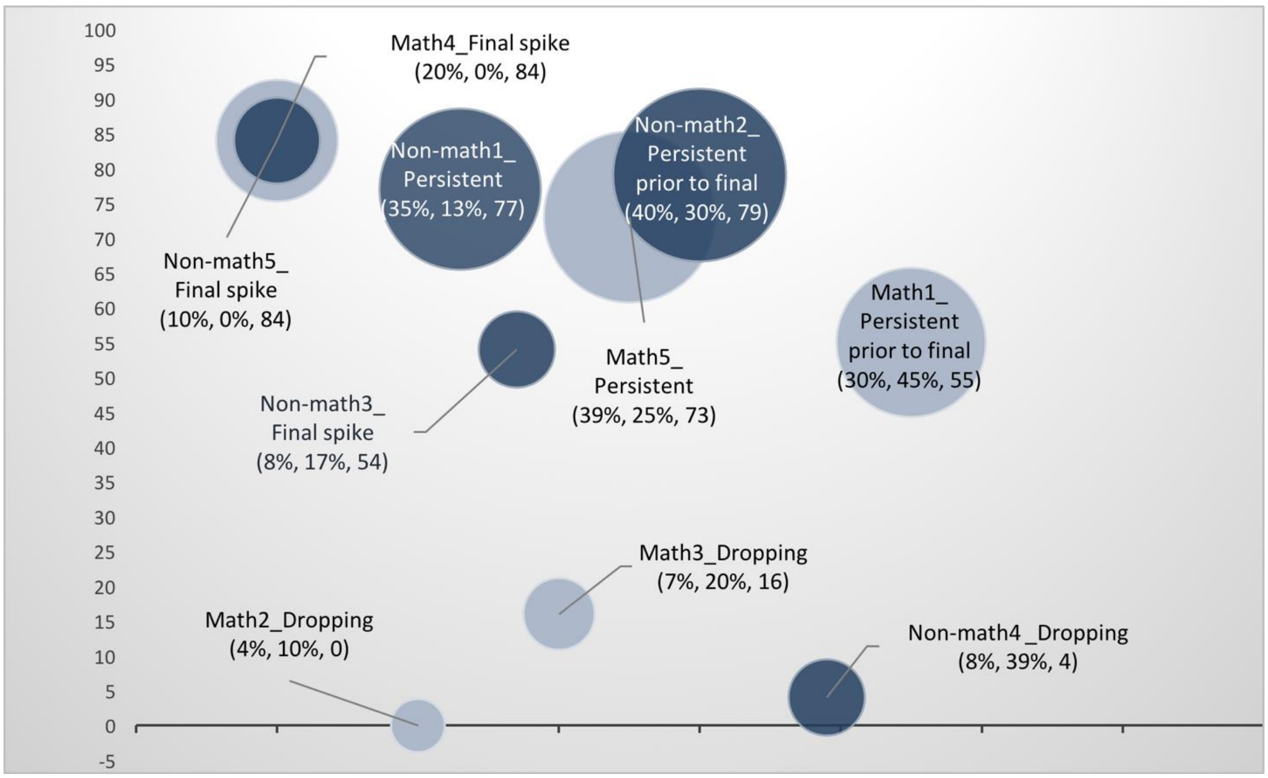
When all 54 mathematics enrollments were grouped into the five clusters, the largest group was Math5 for consistent and persistent course engagement throughout the semester, which comprised 39% of enrollments, none of which were CR cases. The average final grade was 73 out of 100. When it comes to the 119 enrollments in the non-mathematics course, the largest cluster was Non-math2, to which 40% of non-mathematics enrollments, 29% of CR cases, and 33% of passing CR cases were assigned. Their engagement patterns were characterized as gradually increasing until the third quarter of the semester, followed by a gentle slope for the final weeks. Given that week 15's average of attempted scores across members exceeds the passing mark (i.e., 60), many members must have completed the course prior to the final weeks. Note that one-third of passing CR cases were members of this group.

Two groups showing the profile of a final spike, Math4 and Non-math5, have the highest average final grade and no failing cases among its members. Twenty percent of students in mathematics were able to finish the course successfully with a sharp surge in attempted scores during the final weeks, while 10% of students in non-mathematics did the same. The non-mathematics data generated one more cluster for the final spike profile: Non-math3; however, the extent of the final spike (a gap of 41 from week 15 to week 20) was smaller than the other two clusters (a gap of 67 or

64). Each of those three final spike groups contained a CR case, but the Non-math3 was a failing CR case. None of the CR cases were members of the group profiled as de facto dropping out of course.

Figure 2 summarizes clustering results graphically. The horizontal axis presents the percentage of failing cases and the vertical axis shows average final grades across members. Clusters from non-mathematics were marked in a darker color. The data points (i.e., bubbles) in the upper-left region represent clusters with a high final grade and low degree of failing cases while those in the lower-right region represent clusters with a low final grade and high level of failing cases. Data points were labeled using the cluster names and respective profiles; cluster characteristics, such as percentages pertaining to cluster size and failing members, are in parenthesis. The size of bubble corresponds to the cluster size.

Figure 2. Clustering Results of Attempted Scores for Fall Semester

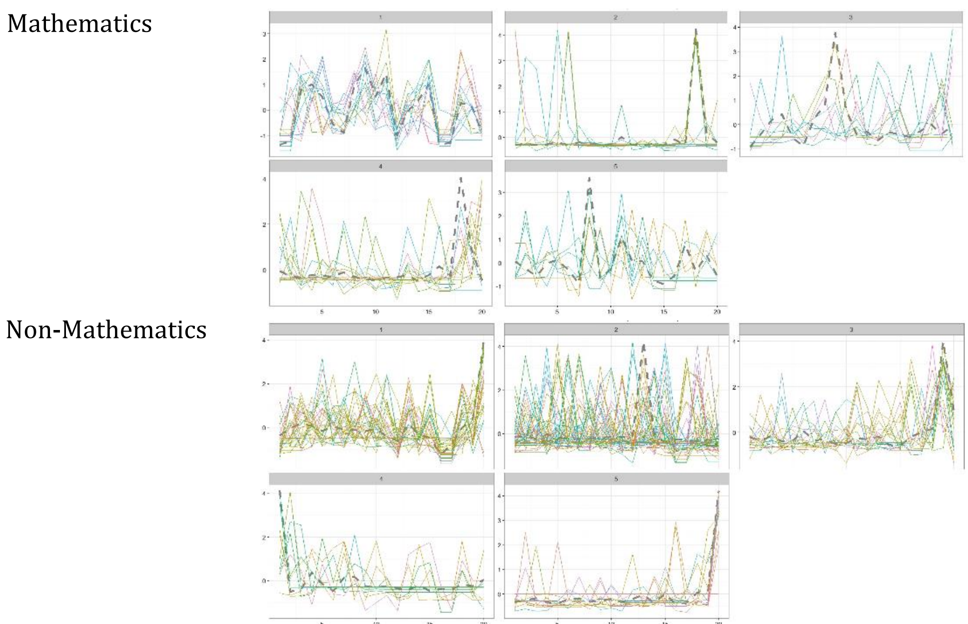


Two clusters with the final spike feature had the highest average course grades, but the mathematics cluster size was greater than the non-mathematics cluster. Both successful final spike groups had members from passing CR cases. Non-math3 reflected the opposite aspect of course outcomes from the final spike profile: low average final grades and a relatively high proportion of failing cases, in particular in the non-mathematics courses. This final spike group included a failing CR case as a member. Although this CR member's intention to complete the course could be deemed from averages of attempted scores at the four time segments (week 5 = 9; week 10 = 24; week 15 = 39; week 20 = 85), the actual earned score fell short of a passing mark.

From both subject areas, the four clusters that were large show persistent course engagement throughout the course or prior to the final weeks. Except for Math1, those clusters' outcomes tend to be desirable (i.e., data points in the upper region). Two non-mathematics clusters appear to show higher average final grades than the corresponding mathematics cluster. For both subject areas, the two clusters profiled as persistent up until the weeks prior to the final week tended to have a greater proportion of failing case members than the clusters that were persistent throughout the semester.

In the next phase of study, week by week totals of minutes that a student recorded in the LMS were explored using the same analytic approach. The five data-driven clusters indicated engagement patterns over the 20 weeks, as shown in Figure 3. The bold dashed line represents members' prototypes of time investment patterns.

Figure 3. Time Series Plot of Time Spent in LMS for Fall Semester



Several peaks in the mathematics cluster (Math1), approximately one in each quarter, demonstrated that members' intensive time investments at certain weeks were repeated. In cluster 5 (Math5), several small peaks and one lofty one stood out, suggesting that during the first three quarters of the semester, the majority of members consistently devoted significant time to the coursework but several members invested significant time occasionally. From the non-mathematics data, the cluster that showed multiple small peaks is cluster 1 (Non-math1). There was a clear distinction between Math5 and Non-math1 — a lofty peak in the final weeks for the latter group.

Meanwhile, groups that showed a lofty peak in a particular quarter were cluster 3 from mathematics (Math3) and cluster 2 from non-mathematics (Non-math2). A lofty peak would indicate a pattern in which the majority of members devoted more considerable time in comparison to the previous time interval. So, Math3's peak in the second quarter of the semester could be interpreted as relatively less time devotion during the first quarter. When it came to Non-math2, a careful observation of the time series plot revealed that at the individual member level (colored line graphs), there were fluctuations across weeks, but the prototype (bold dashed line graph) seemed to stay unchanged before a lofty peak occurred in the third quarter of the semester. This pattern could be construed as the profile in which the majority of members did not show a considerable variation in time investment week over week.

The clusters with a final spike were clusters 2 (Math2) and 4 (Math4) from mathematics and clusters 3 (Non-math3) and 5 (Non-math5) from non-mathematics. Finally, the pattern of more time investment during the early weeks of the semester stands out from the non-mathematics cluster 4's time series plot (Non-math4).

Table 2 presents cluster compositions and a descriptive summary of time spent in the LMS at the four time segments. The size refers to the percentage of cluster members out of the entire sample per each subject area. Four types of percentages are reported: ratios of the number of members to the total study sample, the number of failing case members to the total failing case, the number of CR case members to the total CR case, and the number of passing CR case members to the total passing case. Averages of final grades across members were also included in the summary table. To report the descriptive summary for each of the four time blocks, each case's week-by-week minutes spent in the LMS were totaled up for each quarter (Q1 = weeks 1 through 5, Q2 = weeks 6 through 10, Q3 = weeks 11 through 15, and Q4 = weeks 16 through 20); those sums were averaged across members.

Table 2. Cluster Summary of Time Investment for Fall Semester

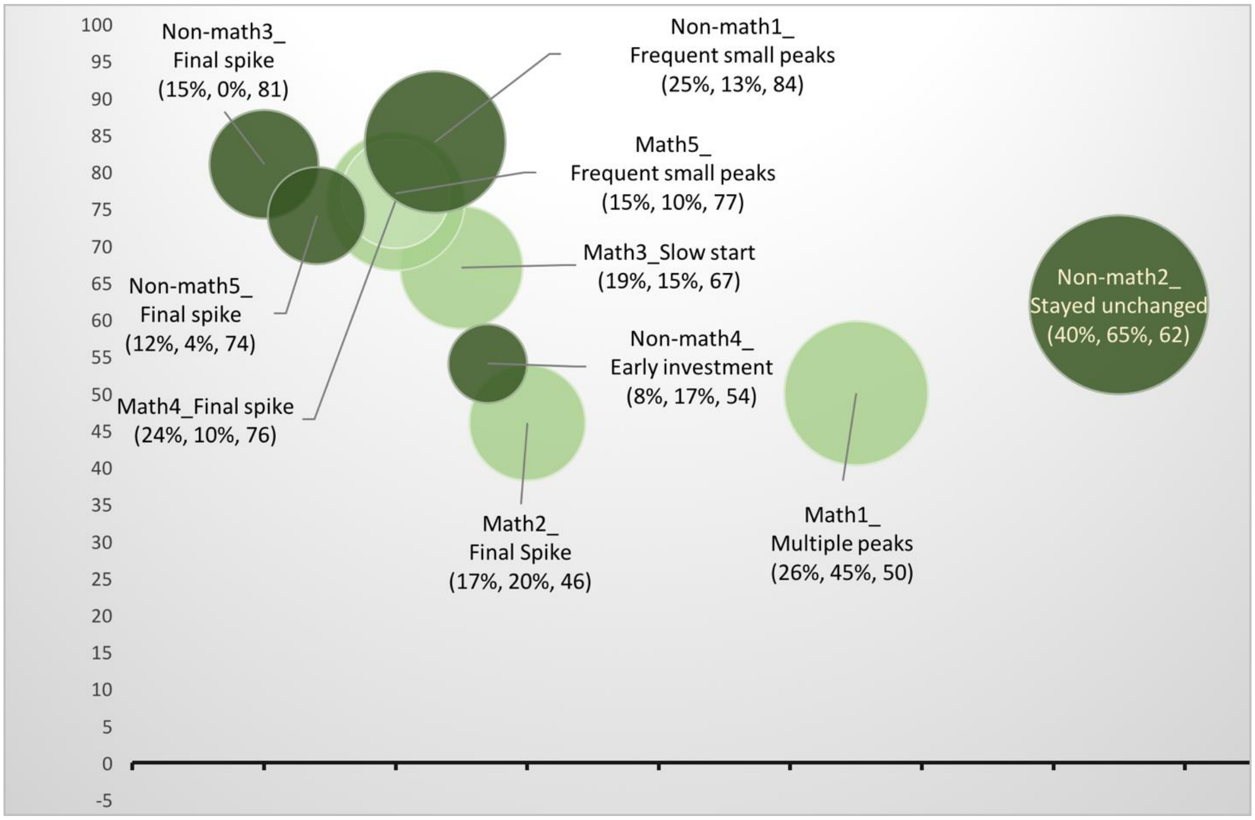
Profile	Cluster	Size	Fail	CR	Pass CR	Avg. Gr.[1]	Q1	Q2	Q3	Q4
Frequent small peaks	Math5	15%	10%	--	--	77	579	610	651	496
Frequent small peaks	Non-math1	25%	13%	50%	56%	84	470	651	516	693
Multiple peaks	Math1	26%	45%	50%	--	50	611	780	611	443
Early investment	Non-math4	8%	17%	7%	11%	54	479	355	261	200
Slow start	Math3	19%	15%	50%	100%	67	275	512	496	613
No variation in prototype	Non-math2	40%	65%	29%	11%	62	304	333	353	261
Final spike	Math4	24%	10%	--	--	76	369	241	192	637
Final spike	Non-math3	15%	--	7%	11%	81	455	458	557	1452
Final spike	Math2	17%	20%	--	--	46	87	25	10	103
Final spike	Non-math5	12%	4%	7%	11%	74	82	144	234	965
Total Count	**Math**	**54**	**20**	**2**	**1**	**--**	**--**	**--**	**--**	**--**
Total Average	**Math**	**--**	**--**	**--**	**--**	**63**	**398**	**449**	**395**	**472**
Total Count	**Non-math**	**119**	**23**	**14**	**9**	**--**	**--**	**--**	**--**	**--**
Total Average	**Non-math**	**--**	**--**	**--**	**--**	**71**	**357**	**412**	**403**	**628**

For mathematics, the largest group was Math1, showing the profile of multiple peaks. Forty-five percent of failing cases were assigned to this cluster, which was far greater than the cluster size percentage. Another type of cluster whose members repeated significant time investments at certain weeks was Math5; it seemed to represent the successful learner profile. Non-math1 also represented successful course completion due to this type of course engagement pattern. A distinction between Non-math1 and Math5 or Math1 was that Non-math1 members had a greater total of minutes during the last quarter of the semester. Non-math1 was the largest group in semesters of passing CR members.

Non-math2 had the largest cluster size among non-mathematics clusters, and one can hardly find specific time points when the majority of members attempted more intensive work, except for a lofty peak during the third quarter. This cluster was more likely to represent the group of poor course outcomes given a greater percentage of failing cases in light of cluster size and the average final grade of 62. By contrast, the most positive course outcomes were found in the clusters whose members showed a lofty peak during the final weeks for both subject areas. As mentioned before, the final spike followed by time investments during the first three quarters of the semester stood out to some degree, and both Math4 and Non-math3 had high averages on the final grade. The only passing CR case was a member of the non-mathematics final spike group. Of the other two groups for the final spike profile, Math2 showed that overall members devoted little time to the course and ended up with a low average final grade.

Figure 4 graphically summarizes clustering results of weekly totals of minutes spent in the LMS. The data points (i.e., bubbles) in the upper-left region represent clusters with a high final grade and low level of failing cases while those in the lower-right region represent clusters with a low final grade and high level of failing cases. Data points were labeled using the cluster names with respective profiles and also cluster characteristics, such as percentages pertaining to cluster size and failing members, in parentheses. The size of the bubble corresponds to the cluster size.

Figure 4. Clustering Results of Time Spent in the LMS for Fall Semester



Three clusters from non-mathematics had relatively greater final grade averages across members. The greatest average was found in the cluster in which members were profiled as significant time investment based on repeating frequent peaks. The mathematics cluster of similar profiles appeared to be smaller in size as well as having lower final grades than the non-mathematics cluster. One clear distinction between the successful mathematics and non-mathematics groups was that the non-mathematics cluster had a surge in the final week following those repeated small peaks. It was notable that 56% of passing CR cases were members of this non-mathematics successful learner group. The averages for CR members at each of four time blocks (420, 433, 396, and 794 in minutes) showed a similar pattern to the cluster averages (470, 651, 516, and 693 in minutes).

Another type of successful learner group could be identified as the final spike profile: in two clusters from the non-mathematics and one from the mathematics. Notably, these groups indicate that consistently considerable time investments were followed by a final spike. However, the mathematics data generated another cluster showing overall less engagement in the course followed by a final spike, which was related to less positive course outcomes. The passing CR members could be found in the two successful final spike groups in the non-mathematics course.

The two largest groups in cluster size for both subject areas were located in the lower-right region, representing the less successful learner group. In the mathematics group's time investment pattern, a lofty peak in each quarter stood out, while for the non-mathematics group, there was not much change in the prototype for the majority of members. These findings suggest that it may be desirable for students to diversify time management according to their level of content mastery, the difficulty level of the content, and the number of tasks assigned.

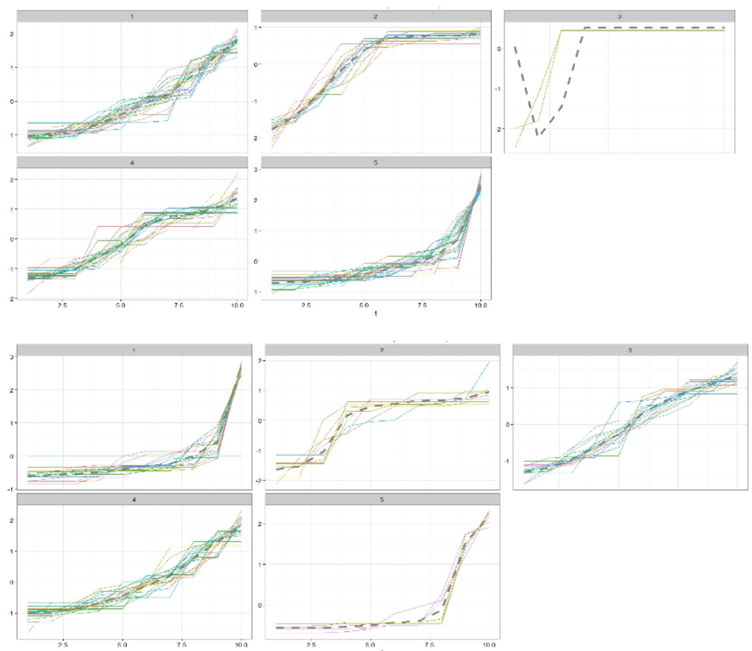
Engagement Patterns in Summer Semester

The summer school offering was 10 weeks in length and included a two-week break. There were 94 enrollment records in total for mathematics, and it contained eight failing cases. Twenty CR enrollment records consisted of four failing and 16 passing cases. With regard to non-mathematics, the total enrollment records of 72 consisted of 20 failing cases. The 23 CR cases contain 16 records from passing cases. The cumulative attempted scores were transformed to the percentage of scores out of the possible score in the course. When clustering time series data into the five groups, individual groups indicated engagement patterns as displayed in Figure 5.

Figure 5. Time Series Plot of Cumulative Attempted Scores for Summer Semester

Mathematics

Non-Mathematics



The patterns of consistent and persistent coursework throughout the semester were found in cluster 1 in mathematics (Math1) and cluster 4 in non-mathematics (Non-math4). But, its gradual increase from the bottom-left corner to the top-right corner did not seem linear, rather it was close to the shape of a half branch of a parabola, suggesting a decline in cumulative score increases during the second and the third quarter of the semester. From non-mathematics, another group with the consistent and persistent coursework feature was found (Non-math 3). Cluster 4 in mathematics (Math4) displayed a plateau in the second half of the semester that followed the persistent coursework pattern in the first half of it.

In three clusters (Math2, Math3, and Non-math2), the increase in cumulative attempted scores stopped after the gradual increase from the bottom-left corner to the top-right corner during the first half of summer semester. This pattern could be related to either early course completion or de facto dropping out of the course in the middle of the semester.

Table 3 summarizes clustering results, including percentages pertaining to cluster size, failing case members, CR case members, and passing CR case members. It also presents averages of final grades across members and averages of attempted scores across members at the four time segments. The time segments were determined as week 2 (W2), week 5 (W5), week 8 (W8), and the final week (W10) per cluster.

Table 3. Cluster Summary of Attempted Scores for Summer Semester

Profile	Cluster	Size	Fail	CR	Pass CR	Avg. Gr.	W2	W5	W8	W10
Persistent in semi-parabola shape	Math1	28%	--	20%	25%	81	0	11	41	80
Persistent in semi-parabola shape	Non-math4	31%	30%	22%	19%	67	1	15	50	78
Persistent work and plateau	Math4	23%	38%	20%	19%	75	1	21	70	79
Persistent throughout semester	Non-math3	24%	10%	17%	19%	82	4	34	72	85
Early completion	Math2	17%	13%	10%	13%	88	1	61	94	95
Less engaged in 2nd half of semester	Non-math2	13%	30%	22%	13%	31	3	26	29	36
Early completion	Math3	2%	--	--	--	92	3	68	68	68
Final spike	Non-math1	25%	25%	39%	50%	68	1	5	15	81
Final spike	Math5	30%	50%	50%	44%	72	1	5	18	41
Final spike	Non-math5	8%	5%	--	--	74	0	2	15	80
Total Count	**Math**	**94**	**8**	**20**	**16**	**--**	**--**	**--**	**--**	**--**
Total Average	**Math**	**--**	**--**	**--**	**--**	**78**	**1**	**21**	**51**	**70**
Total Count	**Non-math**	**72**	**20**	**23**	**16**	**--**	**--**	**--**	**--**	**--**
Total Average	**Non-math**	**--**	**--**	**--**	**--**	**67**	**2**	**17**	**41**	**75**

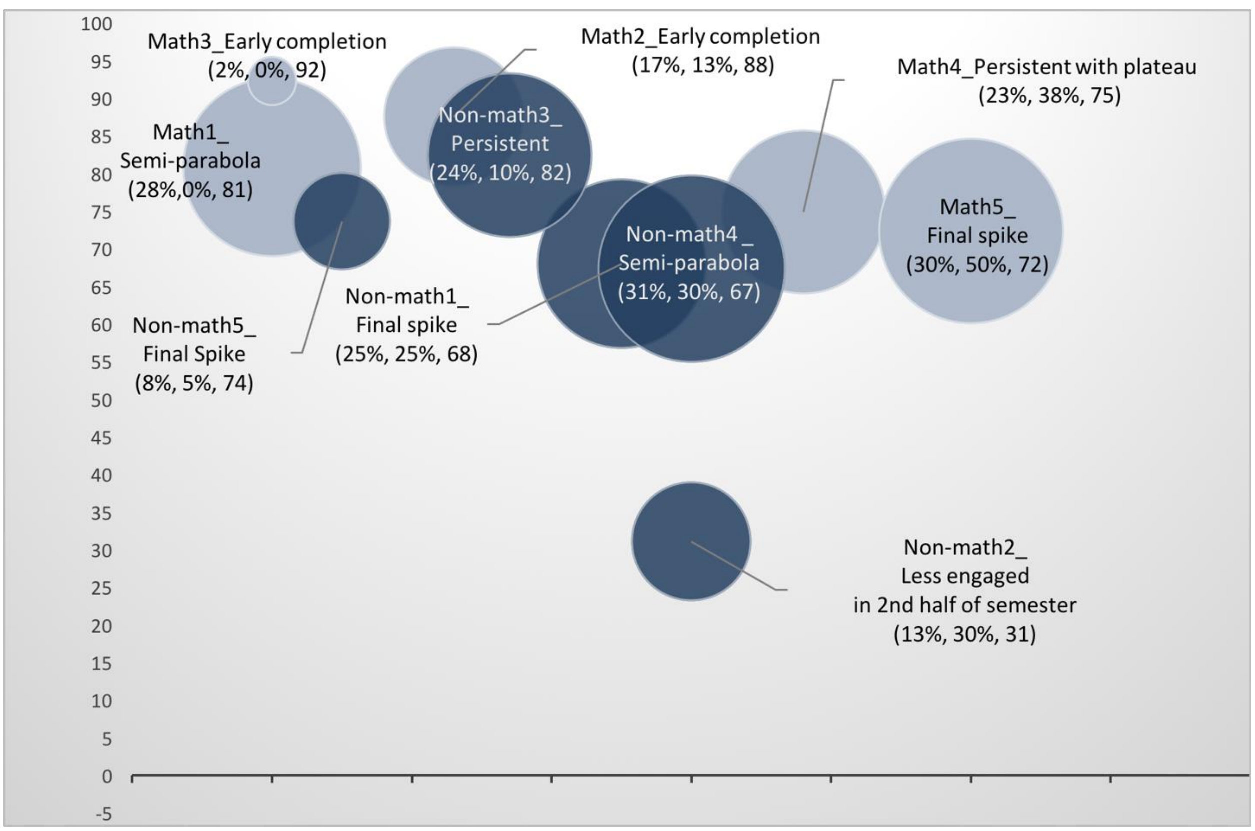
When all 94 mathematics enrollments were grouped into the five clusters, the largest group was Math5 (size = 30%), with various members from failing cases and CR cases. The average final grade was the lowest among the five mathematics clusters. Notably, percentages of CR cases and passed CR cases were the highest in this learner group in which the final surge in attempts to complete the assignment stood out. The second largest group was Math1, and its profile indicated engagement patterns with a brief slow-start, followed by persistent engagement. This group was more likely to represent successful students, given no members were from failing cases, all CR members were from passing CR cases, and they showed a greater average of final grades (81). Finally, we found two early completion groups with the average final grade at a high level.

In the non-mathematics sample of 72 enrollment records, the largest group was Non-math4, showing the profile of a quick slow-start. Its percentage pertaining to members from the failing case (30%) was similar to the size percentage (31%). The second largest group was Non-math1 for the final spike pattern, to which 25% of the entire non-mathematics sample and 25% of 20 failing cases were assigned. Note that eight out of nine CR members were from cases that completed the course successfully and the percentage pertaining to passed CR cases appeared to be the greatest among the five clusters. Cluster 2 was a small group with nine members but could be characterized as a representation of failing students as two-thirds of members were from failing cases.

Among three groups in which the increase in cumulative attempted-scores stopped in the middle of the semester, Math2 and Math3 groups were students who completed the course earlier than the official summer semester, while Non-math2 is related to students whose profiles implied de facto dropping out of the course. Among three final spike groups, Math5 appeared to represent the unsuccessful learner group, and Non-math1 had the largest number of CR members, as well as passing CR members, in the non-mathematics area.

Figure 6 graphically summarizes clustering results of weekly attempted scores. The size of the bubble is related to the cluster size. Being located in the upper-left region denotes more successful learner groups.

Figure 6. Clustering Results of Attempted Scores for Summer Semester



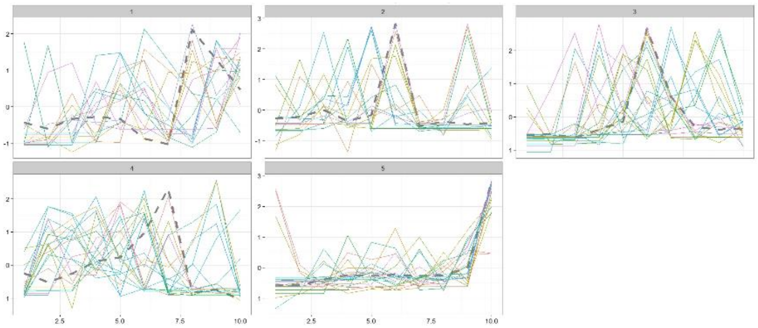
In the upper-left region, Math1 for learners who showed persistent course engagement after a quick slow-start and Math3 for those who completed the course earlier than the official summer schedule can be found. Approximately 30% of the mathematics sample were members of one of those successful learner groups. Passing CR members were found from Math1, but their averages of attempted scores at the four time segments (0, 14, 37, 71) appeared to stay slightly under the cluster averages (0, 11, 41, 80). Of the two groups that stood out in the semi-parabola shape time series plot, Non-math4 was less likely related to positive course outcomes than Math1 was. Non-math4 had CR members from the failing as well as from the passing groups, and their averages (4, 18, 50, 77) at the four time segments tended to be close to the cluster averages (1, 15, 50, 79).

Among three final spike groups, Non-math1's and Non-math4's percentages pertaining to failing members were lower than Math5's which included half of the failing cases in the entire mathematics sample. A considerable number of members from passing CR cases in the respective study sample were grouped in Non-math1 and Math5. There was a difference in CR members' averages of attempted scores at the four-time segments between Non-math1 and Math5. The former group's estimates were close to or greater than the cluster averages (CR: 2, 5, 15, 92; Cluster: 1, 5, 15, 81), while the latter group's estimates were much smaller than the cluster averages (CR: 0, 3, 12, 27; Cluster: 1, 5, 18, 41). It is worthy of note that 13% of the non-mathematics sample (Non-math2) and 30% of the mathematics sample (Math5) fell into one of the learner groups in which members were more likely to show a lack of progress for completing the course during the second half of the semester.

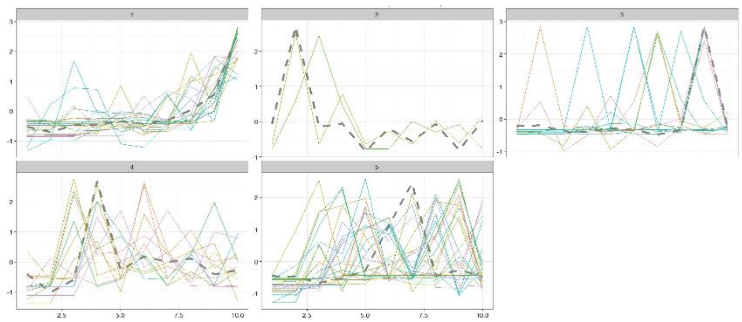
Week by week totals of minutes that a student stayed in the LMS were explored using the same analytic approach. The five data-driven clusters indicated engagement patterns over the 10 weeks, as shown in Figure 7.

Figure 7. Time Series Plot of Time Spent in the LMS for Summer Semester

Mathematics



Non-Mathematics



During the 10-week summer semester, when a lofty peak occurred could distinguish individual clusters' characteristics. The clusters whose lofty peaks exemplified the final spike included clusters 1 and 5 in mathematics (Math1 and Math5) and clusters 1 and 3 in non-mathematics (Non-math1 and Non-math3). Math1 and Non-math3 showed the lofty peak during the final quarter of summer semester while Math5 and Non-math1 occurred during week 10. A distinction between Math1 and Non-math3 could be made from variations in members' time investments before the last quarter of the semester (i.e., the prototype during the first three quarters), revealing more variations for Math1 than Non-math3.

We found three clusters whose peaks appeared in weeks after the first half of summer semester — clusters 2 (Math2) and 3 (Math3) in mathematics and cluster 5 (Non-math5) in non-mathematics. Variations in individual members' peaks show a visual difference between Math2 and Math3. Peaks for some members at various weeks throughout the summer semester were found in Math3's time series plot. In non-mathematics cluster 4 (Non-math4), a lofty peak during the second quarter of the semester and a region of gently rolling hills (small peaks) during the second half of the semester stood out.

The two remaining clusters showed unique patterns on the time series plot. Mathematics cluster 4 (Math4) had a peak at week 7 for the majority of members, with a gentle slope on the left side and a sharp drop on the right side. Except for several members, the majority showed their time investments stopped two weeks prior to the official final week. A conspicuous feature of non-mathematics cluster 2 (Non-math2) was a peak during the first couple of weeks followed by fewer time investments in the course until the final week.

Table 4 presents cluster composition and a descriptive summary of time spent in the LMS at the four time segments. The time segments were determined as W2 for weeks 1 and 2 (2-week interval), W5 from week 3 to week5 (3-week interval), W8 from week 6 to week 8 (3-week interval), and W10 for weeks 9 and10 (2-week interval).

Table 4. Cluster Summary of Time Spent in the LMS for Summer Semester

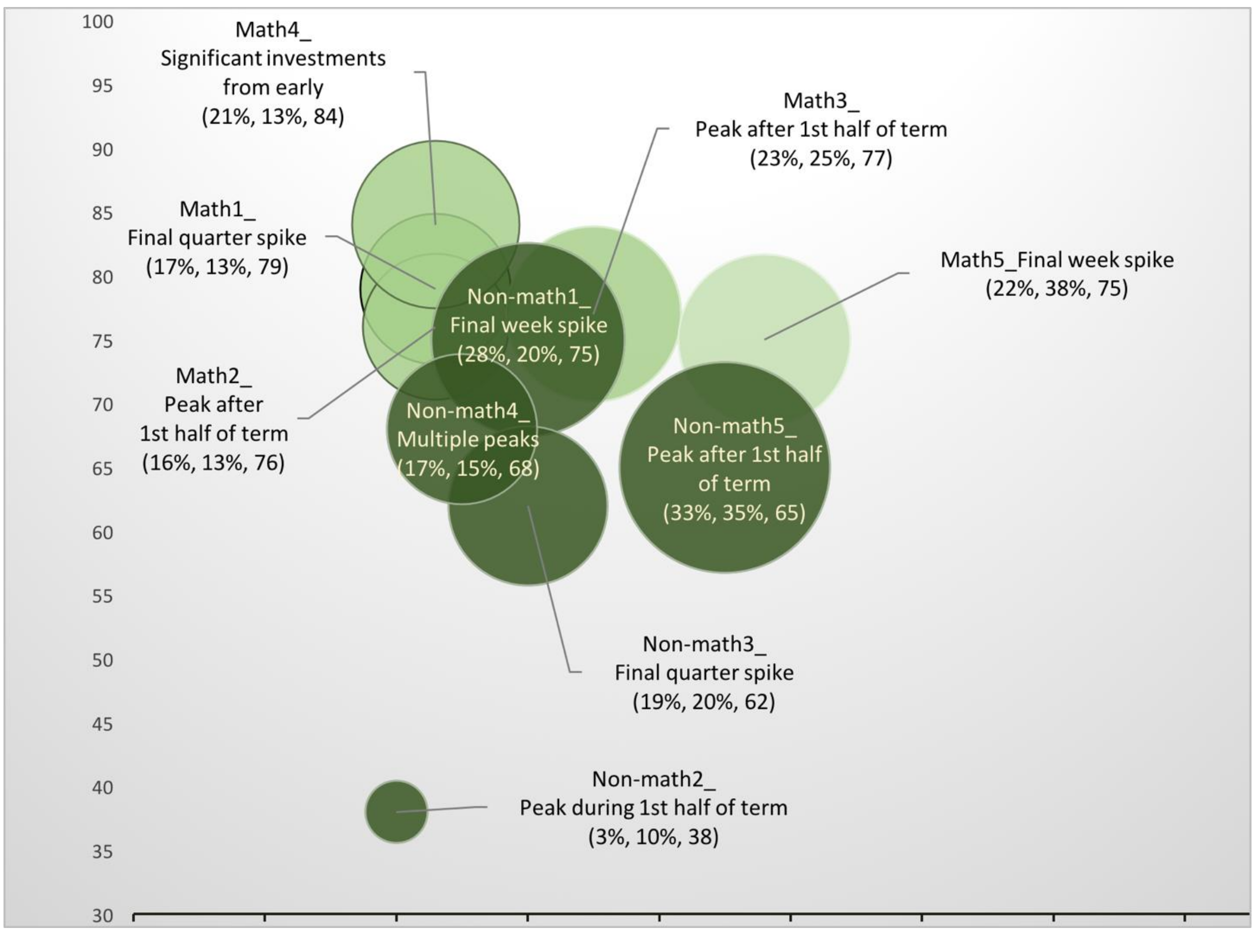
Profile	Cluster	Size	Fail	CR	Pass CR	Avg. Gr.	W2	W5	W8	W10
Final week spike	Math5	22%	38%	45%	38%	75	75	255	282	940
Final week spike	Non-math1	28%	20%	35%	44%	75	94	389	593	1595
Final quarter spike	Math1	17%	13%	10%	13%	79	120	469	670	739
Final quarter spike	Non-math3	19%	20%	22%	19%	62	100	169	693	294
Peak after 1st half of semester	Math3	23%	25%	15%	19%	77	78	565	768	384
Peak after 1st half of semester	Non-math5	33%	35%	22%	19%	65	20	733	840	521
Peak after 1st half of semester	Math2	16%	13%	10%	6%	76	78	565	322	344
Peak during 1st half of semester	Non-math2	3%	10%	4%	--	38	533	724	280	184
Investments from early weeks	Math4	21%	13%	20%	25%	84	446	1092	490	203
Lofty peak and small multiple peaks	Non-math4	17%	15%	17%	19%	68	54	1087	997	445
Total Count	**Math**	**94**	**8**	**20**	**16**	**--**	**--**	**--**	**--**	**--**
Total Average	**Math**	**--**	**--**	**--**	**--**	**78**	**163**	**591**	**513**	**524**
Total Count	**Non-math**	**72**	**20**	**23**	**16**	**--**	**--**	**--**	**--**	**--**
Total Average	**Non-math**	**--**	**--**	**--**	**--**	**67**	**76**	**587**	**754**	**753**

The two largest groups, Math3 and Non-math5, had a time series pattern that featured a sharp surge in time investments after the first half of the summer semester. This characteristic was confirmed by the greatest sum of minutes spent in the LMS from week 6 to week 8 among other possible time blocks. When considering the failing cases proportion in comparison with the cluster size and the cluster average of final grades, neither group seemed to represent the successful learner group. The greatest average of final grades for each subject area was found in Math4 and Non-math1. The profile of Math4 featured a gradual increase in time investments from the beginning of the semester until some weeks prior to the final week, while that of Non-math1 had a sharp surge in time investments during the two final weeks.

There were two groups in which a surge in time investments at week 8 or week 9 stood out. The descriptive summary of totals of minutes spent in the LMS distinguishes between them. That is, Math1 showed members' time investments prior to the sharp surge to some degree, whereas Non-math3 members appeared to have spent less time in the course prior to and subsequent to the spike. This feature explains different course outcomes with the averaged final grade of 76 for the mathematics group and one of 62 for the non-mathematics group.

With increased CR cases in the summer sample, CR case members can be found in all clusters. Forty-five percent of mathematics and 35% of non-mathematics CR cases were assigned to "the final week spike" group for each subject area. These two clusters showed the greatest percentage in passing CR members. The second greatest percentage pertaining to passing CR members was found in the high performing mathematics group as a result of time investments in the course that gradually increased from the beginning of the summer semester until weeks prior to the end of it. The greatest proportion of failing cases was found in Math5 with the profile of final week spike and in Non-math5 with the pattern of a sharp surge in time investments for the majority of members after the first half of semester. Figure 8 depicts clustering results of weekly time spent in the LMS graphically.

Figure 8 Clustering Results of Time Spent for Summer Semester



Three clusters from mathematics had relatively greater averaged final grades and small percentages pertaining to failing case members (i.e., the upper-left region). Math4 had the highest final grade among the 10 clusters and may relate to the profile of time devoted to the course in a gradually increasing fashion from the beginning of the semester to a couple of weeks prior to its end and having a lofty peak during weeks after the midway point of the summer semester. In this successful learner group, CR cases (20% of mathematics CR) were also included, all from the passing cases. Their average of final grades (83) was close to the cluster average, and their time records were slightly below the cluster averages at the first three time segments and marginally above it for the final two weeks (CR averages: W2=372, W5=835, W8=359, W10=243).

The non-mathematics data did not generate this type of cluster related to persistent course engagement and successful course outcomes. Rather, two successful learning profiles were found in the clusters of students who intensively invested time in the course at the final week from the final grade perspective (Non-math1) and for students who had multiple peaks throughout the semester from the failing case assignment perspective (Non-math4). In particular, Non-math1 had CR members (35% of CR cases and 44% of passing CR cases) and their average of final grade was slightly above the cluster average (75) while the averages of time spent at the four time segments were below the cluster averages for the four time segments (CR member averages: W2=93, W5= 218, W8=250, W10=1384).

Except for a small cluster, there were two groups related to the relatively low performance (i.e., the lower-right region). Math5 demonstrated a stark difference in time investments between the first three time segments and the last one, which is profiled as the final spike group, while Non-math5 showed relatively fewer time investments during the first half of the semester. Math5 was the largest mathematics group regarding the CR member proportion, and CR members had a lower average of final grades (66) than the cluster average. Their time investments shared the cluster prototype but tended to rely more on the final spike (CR averages: W2=20, W5=283, W8=367, W10=1,039). Non-math5 also included CR cases as members, and their average final grade (45) was far lower than the cluster average (65). The degree of time investments for CR members was extremely low (CR averages: W2=1, W5=261, W8=273, W10=212).

Discussion

Two previous reports in this series applied time series clustering methodology to the two types of course-activity data, namely weekly data on both the students' attempted scores and the number of minutes spent in the LMS focused on the first part of an Algebra 2 course. The current report extended the work exploring students' coursework behaviors and thereby learning profiles to other subject areas most frequently taken by CR students: Algebra 1, English Language & Literature 9, and U.S. History & Geography 1. The discussion section will synthesize key findings by providing a benchmark for the optimal coursework behaviors. A data-driven benchmark such as this may give guidance to instructors and mentors in monitoring the student's course engagement and progress over the weeks.

The fall semester attempted score data generated a successful final spike group in the mathematics course with the greatest average of final grade among the mathematics clusters and a relatively small proportion of members from failing cases, approximately 20% of the study sample. This group had passing CR students as their members. However, the cluster size indicated this type of learning profile did not apply to the majority learners in the course. Furthermore, non-mathematics data generated two types of final spike groups from the course outcomes' perspective: one for the successful and the other for the less successful. This result suggests that only some students in non-mathematics courses were capable of attempting and earning enough points to pass in final weeks of the course.

Meanwhile, the largest groups for each subject area turned out to demonstrate persistent engagement throughout the semester to complete the course by the final week or earlier than that. For both areas, the course outcomes appeared to be more favorable when persistent coursework was maintained to the end of the semester. Taken together, the "persistent course engagement throughout the semester" and its passing members' estimates were selected as a data-driven benchmark for the attempted-score during the fall semester. The estimate is the ratio of attempted scores to the full course points in percentage at the four-time segments of weeks 5(W5), 10(W10), 15(W15), and 20(Final).

- Mathematics/Persistent engagement for the entire semester: W5 = 13%, W10 = 36%, W15 = 59%, Final = 94%
- Non-mathematics/Persistent engagement for the entire semester: W5 = 14%, W10 = 30%, W15 = 54%, Final = 91%

The passing CR member in non-mathematics shared not only the time series pattern (i.e., persistent coursework throughout the semester), but also showed estimates of attempted-score close to this benchmark (W5 = 12%, W10 = 26%, W15 = 55%, Final = 91%). By contrast, the failing CR case's degree of efforts fell well below this benchmark, despite its similar time series pattern (W5 = 5%, W10 = 12%, W15 = 15%, Final = 25%). No CR case was included in mathematics group members. From another cluster, one failing CR case showed the level of course engagement far below the benchmark (W5 = 3%, W10 = 5%, W15 = 14%, Final = 16%) while the passing CR case seemed an exceptional case that was capable of completing assignments in a few final weeks (W5 = 5%, W10 = 14%, W15 = 35%, Final = 87%).

When it comes to time investment, the two largest groups for each subject area were located in the lower-right region, which represented the less successful learner group. In the mathematics group's time investment pattern, a lofty peak in each quarter stood out while in the non-mathematics group, the prototype for the majority of members remained stable. These findings suggest that it may be desirable for students to diversify time management according to their level of content mastery, the difficulty level of content, and the number of assignments provided at a certain time. Positive course outcomes were found in two types of engagement patterns for both subject areas: time investments to some degree followed by the final spike and the overall significant time investments by frequently repeating small peaks. Among those, one with a larger cluster size was chosen as the benchmark: the final spike for the mathematics and the consistently significant time investments for the non-mathematics. Passing members' averages on totals of minutes spent in the LMS for the five-week blocks (Q1 for weeks from 1 to 5, Q2 for weeks from 6 to 10, Q3 for weeks from 11 to 15, and Q4 for weeks from 16 to 20) as follows.

- Mathematics/Final spike: Q1 = 386, Q2 = 271, Q3 = 227, Q4 = 750

- Non-mathematics/Frequent small peaks: Q1 = 464, Q2 = 668, Q3 = 528, Q4 = 668

The non-mathematics group had CR cases as part of its members because they share similar engagement patterns. However, their degree of engagement seemed different from the benchmark above. For example, passing CR members' degree of engagement fell well below the benchmark for all of four time blocks (Q1 = 405, Q2 = 461, Q3 = 373, Q4 = 609). In the failing CR members' degree of engagement, a surge in time investment at the final quarter stood out, although they were members of the profile of frequent small peaks in conformity with the entire time series pattern (Q1 = 458, Q2 = 364, Q3 = 453, Q4 = 1257). There is no CR member for the mathematics group, and the extent of time investment fell well below the benchmark not only for the failing CR (Q1 = 387, Q2 = 256, Q3 = 192, Q4 = 40) but also for the passing CR (Q1 = 201, Q2 = 78, Q3 = 166, Q4 = 334).

In analyzing the summer data, we found more various types of successful learner groups in the mathematics sample than in non-mathematics. CR students appeared to be included in those successful groups, except for the early completion group in mathematics. Approximately 30% of the mathematics sample were members of one of those successful learner groups profiled either as persistent course engagement after a quick slow-start or as the earlier completion than the official summer schedule. In addition, 17% of the mathematics sample also showed an early completion profile by exceeding the passing mark in the middle of the summer semester and then continuing coursework through the end of the semester. This cluster had several members from the failing cases, but the cluster average of final grade was high. Meanwhile, the successful learner group in non-mathematics appeared to hold the profile of consistently persistent coursework throughout the summer semester. Taken together, engagement patterns of passing members from the "persistent course engagement followed by the quick slow-start" cluster in mathematics and "persistent course engagement throughout the semester" were selected as benchmarks of attempted-score in the summer semester.

- Mathematics/Slow start and then persistent engagement: W2 = 0%, W5 = 11%, W8 = 41%, Final = 80%
- Non-mathematics/Persistent engagement for the entire semester: W2 = 4%, W5 = 37%, W8 = 80%, Final = 94%

The mathematics group had CR members from passing cases, and their averages were below the standard indicated above (W2 = 0%, W5 = 14%, W8 = 37%, Final = 71%). On average, the non-mathematics' passing CR members had similar estimates to the benchmark (W2 = 0%, W5 = 43%, W8 = 82%, Final = 84%), but the failing CR members' estimates were well below it (W2 = 0%, W5 = 10%, W8 = 21%, Final = 23%).

Observations of clustering results from the time-spent data demonstrated three types of successful groups in mathematics. It included profiles such as gradually increasing in time investments from the beginning of the summer semester to several weeks prior to the final, having a surge in time investments after the first half of the semester, and having the last spike during the several final weeks. Among those clusters, the first one offered a benchmark against which the student's time investments in summer mathematics courses should be monitored. The non-mathematics data resulted in the most positive course outcomes for the final spike group from 28% of the non-mathematics sample.

- Mathematics/Significant time investments from the beginning of the semester to the several weeks prior to the final: W2 = 454, W5 = 1099, W8 = 467, Final = 214
- Non-mathematics/Persistent for the entire semester: W2 = 109, W5 = 433, W8 = 707, Final = 1608

In the mathematics benchmark group, no failing CR member was assigned, and the passing CR members' estimates on time-spent during the two- or three-week block were slightly under the benchmark for the first three time blocks (W2 = 372, W5 = 835, W8 = 359, Final = 243). The non-mathematics group's passing CR members also revealed a degree of time investment that fell slightly below the benchmark, despite their similar time series patterns (W2 = 93, W5 = 222, W8 = 286, Final = 1273). The failing CR members' averages appeared to be characterized by extreme dependence on the final spike (W2 = 99, W5 = 187, W8 = 1, Final = 2156).

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