Exploring Patterns of Time Investment in Courses

Time Series Clustering Analysis

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MICHIGAN VIRTUAL LEARNING®
RESEARCH INSTITUTE

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 will place more fine-grained variables at the analytic center by examining students' engagement patterns in their courses. The 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

The second and third reports in this series are devoted to examining behavioral indicators, and thereby suggesting how students, including those whose enrollment reason was credit recovery (CR), engaged in the first part of an Algebra 2 course. Among the two types of behavioral indicators, namely students' attempted scores and the number of minutes spent in the learning management system (LMS) on a weekly basis, the current report presents results from exploring the latter, the variable of academic time. With Algebra 2A LMS data in the 2015-16 academic year, time series clustering was used, which partitioned time series data into groups based on differences or similarities among data points, and in turn generated learning profiles.

Clustering results indicated that the majority of students, regardless of enrollment reasons, were members of the group in which an intensive time investment during the final weeks stood out, whereas a small minority of students were assigned to the group that featured multiple occurrences of intensive time investment over academic terms of either 10 or 20 weeks. Some CR cases were found in the majority group, but they were often assigned to the groups that were profiled as having no peaks in the final weeks or featuring early course work time investments when the semester started. Spring semester results indicated that the CR students were also assigned to one of the two clusters whose members invested time at either the beginning or the end of the semester. When it comes to course outcomes, some students, including CR students, could not achieve such desired outcomes as fast pacing and subsequent successful course completion, even after an intensive time investment in the first half of the academic term. During the short academic term of summer semester, most failing CR members showed time records that were well below their cluster averages. In contrast, the three passed CR members' time investment was more likely to exceed the cluster averages for at least one quarter. Those findings were discussed in literature on academic learning time.

Introduction

In an attempt to accumulate empirical evidence related to student learning focused particularly on those who took courses for credit recovery (CR) purposes, *MVLRI* has launched a series of quantitative research reports. The first report[1] demonstrated CR students' final outcomes were significantly different from students whose enrollment reasons were other than CR. Those findings guided the next step of the study: a subject area most frequently taken by CR students was chosen, and how student learning behaviors looked in the course became a central part of the research.

Time series clustering methods enabled us to identify meaningful learning profiles by exploring variables that represent course engagement patterns. Using this analytic approach and the behavioral indicator from the gradebook data – week-by-week students' attempted scores – the second report in the series presented that the majority of students, including CR cases, showed

[1] Kwon, J. B. (2017). *Examining credit recovery experience at a state virtual school*. Lansing, MI: Michigan Virtual University. Retrieved from https://mvlri.org/research/publications/examining-credit-recovery-experience-at-a-state-virtual-school-2/

persistent and consistent engagement patterns in the first part of their Algebra 2 course. Despite course engagement occurring in a positive way, members' course outcomes were mixed. Study findings suggested that metacognition components should be integrated into the course design as well as instructional practices. Furthermore, findings from summer semester data highlighted the importance of a relationship with an academic mentor. For the third report in the series, the current study followed the same procedures as those followed in the second study, but used a different time series variable, weekly sums of minutes spent in the course, from the learning management system (LMS) timestamped records. For information on methods and data, see the second report[2].

Learner activities are crucial for successful online learning, and the LMS makes a large amount of data on those activities readily accessible to researchers. In the K-12 context, the variables that have often been targeted by researchers include how often the student logged in to the system and how much time was spent within it. Using hierarchical linear modeling, for example, Liu and Cavanaugh (2011) found that the time students spent in the LMS was significantly associated with the final score in frequently enrolled-in subjects such as Algebra, Geometry, the second part of English 2, American History, and American Government. Despite the implications of the study mentioned above, this type of aggregation approach (i.e., the total frequency of log-ins or content access and accumulated time spent for the period of the entire academic term) tends to underestimate variances in learning patterns over time. An approach that reflects situational influences in the learning process, such as a time series analysis, enables us to identify patterns between more than one attribute that might lead to a student's success or failure and to capture key aspects of intra-individual changes in the learning process.

There is another aspect of data that validates our analytic approach: focusing on patterns by using time series approach. Regardless of course format (i.e., face-to-face or online), data on time spent hardly captures a student's pure time engaged in learning. Data on time in class often has a measurement error, for example, if some minutes were devoted to class or behavior management. Also there is no guarantee that the student was fully engaged in academic activities that occurred in class. In the context of online courses, time spent in the LMS represents an imperfect measure in that it only records student activity within the LMS. Time spent on materials off-line or outside the LMS through embedded URLs (e.g., video clips) cannot be stored in the database. Even LMS records suffer from the potential problem that the student may or may not have been working on the course content the entire time that content was being displayed.

This matter was confirmed by empirical evidence. For instance, Macfadyen and Dawson (2010) investigated various LMS tracking variables' predictive power on the student final grade and found a relatively lower level of correlation from variables related to time-spent-data (e.g., time spent on assignments $r = 0.14$ and time spent on assessments $r= 0$) than others (ranging from the total

[2] Kwon, J. B. (2017*). Examining Credit Recovery Learning Profile from Time-Series Clustering Analysis of Attempted Scores*. Lansing, MI: Michigan Virtual University. Retrieved from https://mvlri.org/research/publications/examining-credit-recovery-learning-profile-time-series-clustering-analysis/

number of discussion messages posted $r = 0.52$ to the total number of mail messages read $r = .22$). Accordingly, it is desirable that time-spent-data should be explored focusing on trends or patterns in observations measured successively.

Therefore, the present study centered on the time series variable, weekly time spent in minutes. After hierarchical clustering was performed, individual clusters' compositions and corresponding time series were explored based on key factors of interest, such as enrollment reason (focused on CR) and learning outcomes. The study defined student proportions of earned course scores to scores suggested by the pacing guide at five time points when progress was checked (i.e., checkpoint 1, checkpoint 2, checkpoint 3, checkpoint 4, and the final week). Research questions that guided the study are as follows:

- When the weekly time spent in the LMS is used as a measure of inter-subject similarity, how are the clusters formed?
- After the clusters have been formed, how are the clusters defined using summary measures, including weekly earned scores and final grades, in a descriptive sense?

Results

The second behavioral indicator of effort is how long a student spent in the course each week. Using the same time protocol to structure time series as the one used with weekly attempted scores, the time in LMS specific to Algebra 2A courses in minutes was analyzed. Note that the time series of weekly attempted scores was based on cumulative scores, but the data for time spent in the LMS was coded with distinct figures for each week, by which the time series plot does not necessarily create the uptrend. Obtained clusters' time series charts were explored based on peaks and troughs of the prototype (bold dashed line graph). Peaks on the plot indicate increases in time in the LMS that would occur when the majority of members show an overall rise in the data or when there is a steep rise in some members' data. A downward trough represents less time spent in the LMS, for example, if the smaller number of members show a peak, if the degree of individual members' peaks is smaller when the current time point value is compared to the previous one, and/or when individual members' gradual decrease in the data stands out. For the hierarchical clustering result for individual academic terms, see the dendrogram in the Appendix.

Fall Semester

When the data of 72 enrollment records and their time spent in the LMS were introduced, time series clustering generated the five clusters with the composition shown in Table 1.

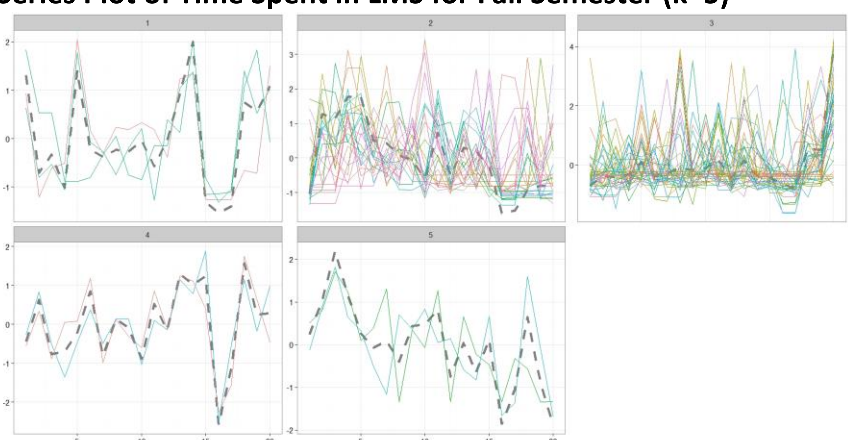
Table 1. Cluster Summary of Fall Semester (k=5)

Cluster	Size (#)	Size (%)	Failing (#)	Failing (%)	CR Case (#)	CR Case (%)	Passed CR (#)	Passed CR (%)
1	3	4%	1	7%	1	33%	--	--
2	24	33%	4	29%	2	67%	1	100%
3	41	57%	9	53%	--	--	--	--
4	2	3%	--	--	--	--	--	--
5	2	3%	--	--	--	--	--	--
Total	**72**	**100%**	**14**	**100%**	**3**	**100%**	**1**	**100%**

Of the five clusters, the largest one was Cluster 3 in which 57% of fall enrollments were included with a similar proportion of failing cases (53% of 14 failing cases). None of the CR enrollments were assigned to this learning profile group. This is in contrast to findings in the second report of this series that all three CR cases were assigned to the largest group when clustering was performed by weekly-attempted-scores. CR enrollments appeared to be members of either of the two groups, Cluster 1 or Cluster 2. Cluster 2 was the second largest group (33% of 72) and contained 29% of failing cases, including one failing and one passing CR case.

Figure 1 presents the time series plot for each of the five clusters. Comparing the shape of the trends informs how each cluster's members spent time in the LMS. The bold dashed line is members' prototypes of time investment for the course.

Figure 1. Time Series Plot of Time Spent in LMS for Fall Semester (k=5)



From the largest group, Cluster 3, one of the most salient features is the sharp peak at the final week. Some members appear to have several peaks (graphs in color), but the prototype (bold dashed line graph) demonstrates members' intensive coursework during the last quarter of the academic term. This is in contrast to the previous study's results wherein the weekly-attempted-score data was explored using the same clustering strategy and for the same enrollment records, which found the persistent learning profile to be the largest group. Of the two groups of small numbers of members with successful results, Cluster 4 represents consistent time investment at a relatively high level throughout the course term, while Cluster 5 has an overall downward tendency following active engagement during the first quarter of the term.

In Cluster 2's time series plot, a lofty peak followed by a downward trough stands out, suggesting that the majority of members devoted considerable time to the coursework during the first half of the fall semester. Two relatively small peaks are also shown in the third quarter of the academic term. The final spike does not stand out as a representative characteristic among Cluster 2 members.

The three groups of small cluster sizes show (a) several peaks demonstrating members' intensive coursework at the beginning of the semester as well as prior and subsequent to the winter break in Cluster 1, intensive time investment at the beginning of the semester and a gradual decrease in time records as moving toward its end in Cluster 5, and frequent small peaks throughout the course term in Cluster 4.

Profiles from plots are consolidated in the descriptive summary shown in Table 2 that reports the averages of total minutes across members within the four time blocks, including weeks 1 to 5 (Q1), weeks 6 to 10 (Q2), weeks 11 to 15 (Q3), and week 16 to the final week (Q4).

Table 2. Descriptive Summary of Time Spent in LMS for Fall Semester (k=5)

Cluster	Avg. of Q1 Sum[1]	Avg. of Q2 Sum	Avg. of Q3 Sum	Avg. of Q4 Sum
1	1,062	684	1,082	988
2	753	749	596	402
3	447	465	487	932
4	854	894	1,222	812
5	1,114	755	681	251

Note1: The sum of minutes recorded within specified quarters was averaged out across cluster members.

Each cluster's statistics appear to be in accord with patterns captured by plots. For instance, the final spike group (Cluster 3) had an increase in the member average from Q3 to Q4 time blocks while all other clusters showed a decrease. Also, the gradual decrease group, Cluster 5, had the highest records with the members' average of total minutes during the first quarter of course term (1,114 minutes) while also having the lowest average sum for the last quarter.

When the cluster number is specified at 10, the aforementioned clustering results for Clusters 1, 4, and 5 (k=5) remain the same for Clusters 1, 8, and 9 (k=10). Table 3 reports results.

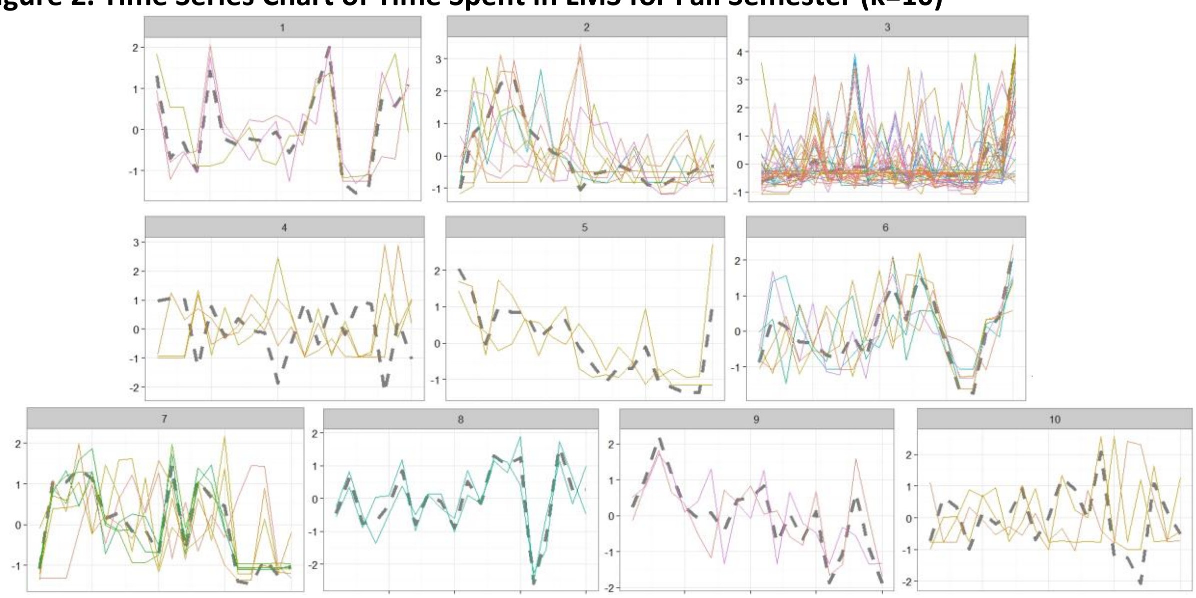
Table 3. Cluster Summary of Fall Semester (k=10)

Cluster	Size (#)	Size (%)	Failing (#)	Failing (%)	CR Case (#)	CR Case (%)	Passed CR (#)	Passed CR (%)
1	3	4%	1	7%	1	33%	--	--
2	9	13%	3	21%	2	67%	1	100%
3	35	49%	9	64%	--	--	--	--
4	3	4%	1	7%	--	--	--	--
5	2	3%	--	--	--	--	--	--
6	6	8%	--	--	--	--	--	--
7	7	10%	--	--	--	--	--	--
8	2	3%	--	--	--	--	--	--
9	2	3%	--	--	--	--	--	--
10	3	4%	--	--	--	--	--	--
Total	72	100%	14	100%	3	100%	1	100%

Among the 10 obtained groups, the largest group was Cluster 3 (49%), whose members were all non-CR cases and which included the greatest number of failing cases (64%). Clusters 6 (8%) and 7 (10%) were relatively small clusters and contained only successful learners. Two CR cases were assigned to the second largest group, Cluster 2 (13%), and this cluster's percentage pertaining to failing cases (21%) is larger than the cluster size percentage.

Figure 2 present results of time spent in the LMS over the 20 weeks for the 10 clusters.

Figure 2. Time Series Chart of Time Spent in LMS for Fall Semester (k=10)



The largest cluster's learning profile, Cluster 3, is represented by a narrow peak in the final quarter of the term and a relatively low level of overall time investment, indicating intensive time investment during the final weeks. Cluster 7 is characterized by a broad peak ranging from the first to the tenth week and another considerable investment of effort during the third quarter of the academic term, resulting in the coursework being completed prior to the final weeks. Another profile for successful learners was Cluster 6, involving a small peak at the beginning of the semester and a considerable investment of time during the third quarter of the term and at the final week. CR students were not found in either of the two clusters for successful learning.

The two clusters whose members included CR enrollment cases showed peaks in the first and third quarters (Cluster 1) or a broad peak ranging from the first to second quarters of the academic term. A small minority of students (7%) appeared to be assigned to two groups having successful results after engagement patterns of one or more small peaks in each quarter of the term (Cluster 10) or intensive coursework during the first half of the academic term (Cluster 5).

Table 4 reports the averages of total minutes across members within the four time blocks for the 10 clusters.

Table 4. Descriptive Summary of Time Spent in LMS for Fall Semester (k=10)

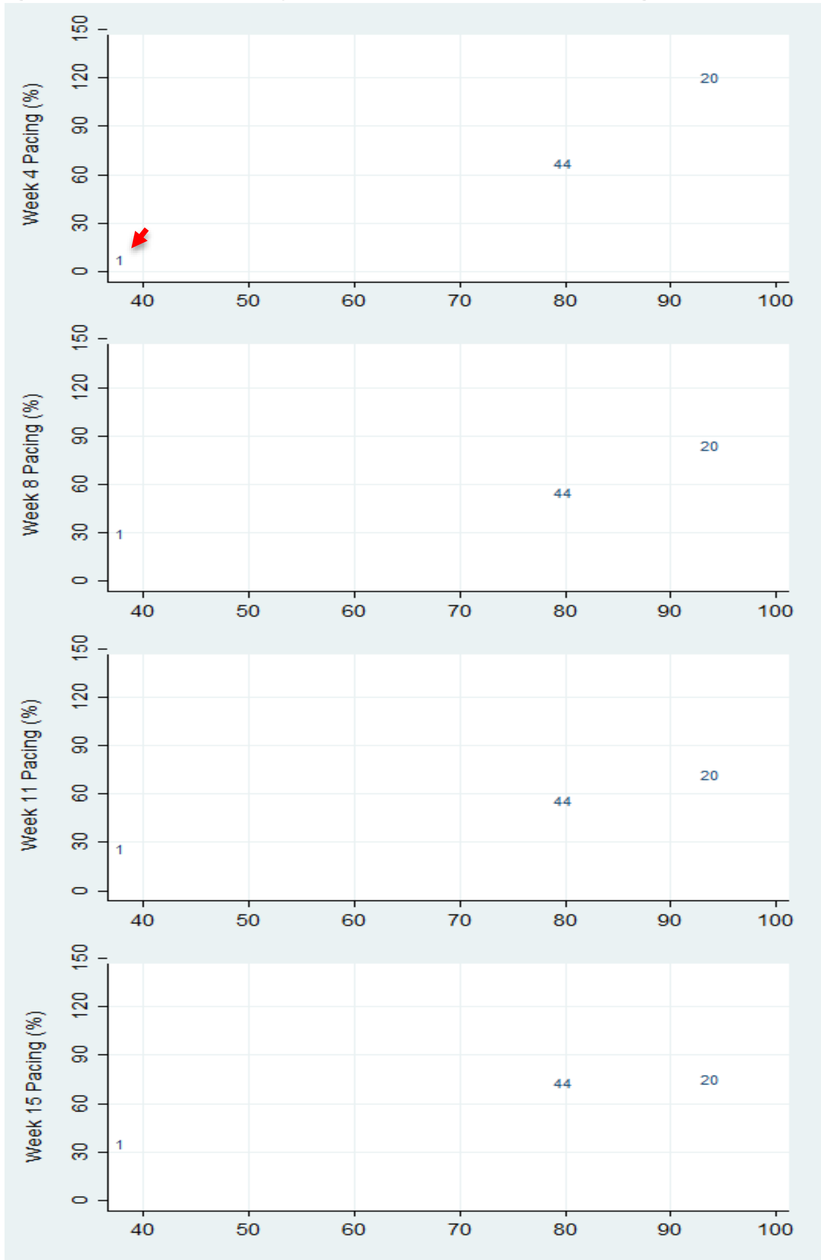
Cluster	Avg. of Q1 Sum[1]	Avg. of Q2 Sum	Avg. of Q3 Sum	Avg. of Q4 Sum
1	1,062	684	1,082	988
2	750	696	464	207
3	414	439	388	970
4	382	837	472	695
5	1,640	1,235	514	485
6	639	614	1,065	710
7	743	753	813	360
8	854	894	1,222	812
9	1,114	755	681	251
10	993	785	603	637

Note1: The sum of minutes recorded within specified quarters was averaged out across cluster members.

Profiles based on time series plots were fleshed out by members' averages of total minutes spent in the LMS during particular quarters of the academic term. For instance, an increase from Q3 to Q4 demonstrates Cluster 3's profile of a final spike and higher averages in the early time periods and corresponds with a broad peak over the first 10 weeks for Cluster 2 or Cluster 7.

Using the same method that was used for weekly attempted scores in the second report of this series, learning outcomes were observed for the clusters into which any CR cases were assigned. Each figure contains four scatter plots of proportion of earned scores to pacing guide standards against the final score for each of four progress check points. The scatter plot consists of the vertical axis presenting the percentage of points earned by the student at each progress-check points as a percentage the pacing guide standards while the horizontal axis indicates the final score that is consistent across the four plots. The data points in the upper-right region represent students with high final scores who also stuck to or moved ahead of the pacing guide recommendations, while those points in the lower-left region represent students with low final scores who fell behind the pacing guide recommendations. Figure 3 and Figure 4 present results of Cluster 1 and Cluster 2, respectively for each of four progress check time points.

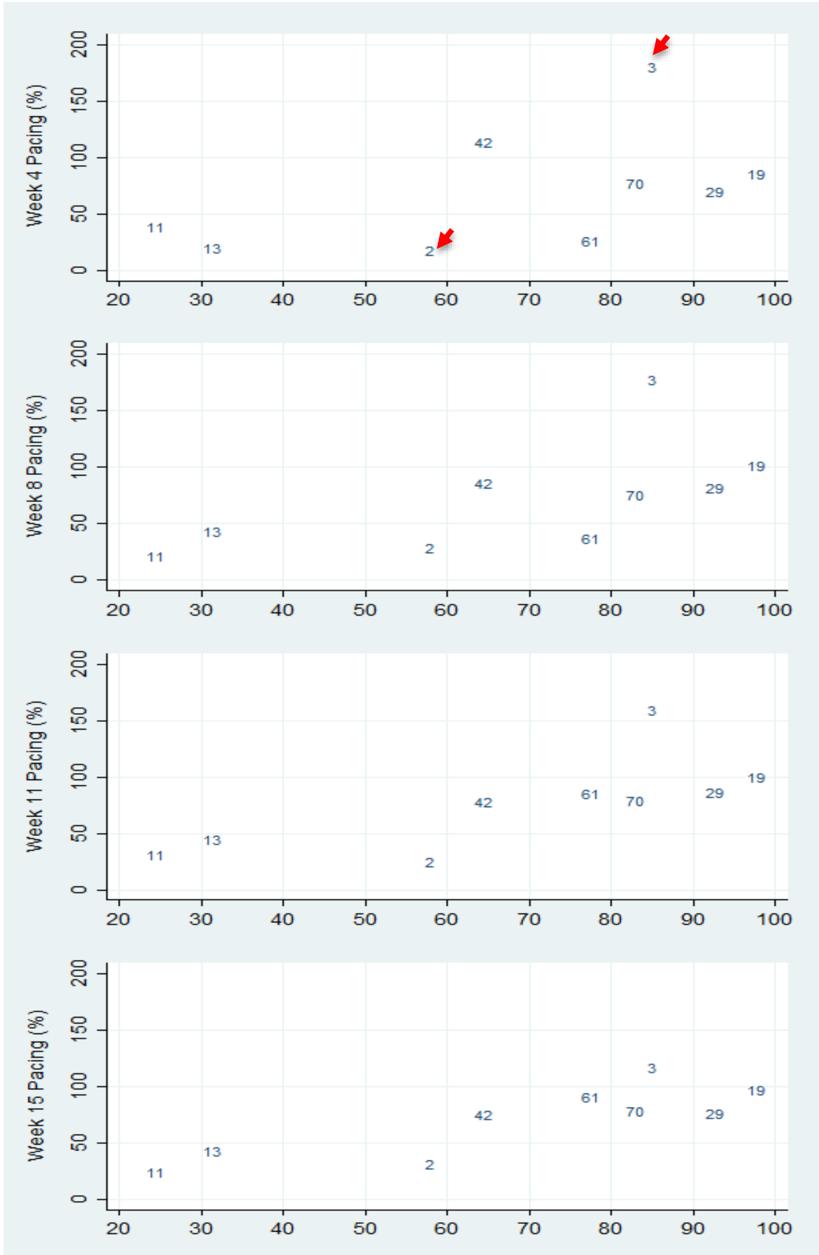
Figure 3. Learning Outcome Summary of Cluster 1 – Peaks during Q1 and Q3 (k=10, CR=1)



Note. The CR case data point has been marked by 1.

Cluster 1, into which one failing CR case was assigned, demonstrates learning outcomes with a final grade of 70% and the proportion of earned scores to the pacing guide standard ranging from 50% (Pace 3) to 64% (Pace 1) across the four progress check points on average across the three members. The CR case is distinct from the other two members in terms of even slower pacing, leading to course failure. It is notable that those members could be grouped based on similar patterns of data distribution on the time series but the CR student appears to have spent the least amount of time among the members. Based on those facts, one could logically assume that controlling time investment by rotating between high and low intensity does not ensure course success, in particular for CR students whose overall time investment is at a low level.

Figure 4. Learning Outcome Summary of Cluster 2 – No Peak in the Final (k=10, CR=2)



Note: The CR case data points have been marked by 2 and 3.

Cluster 2 members, including one failing and another passed CR case, show learning outcomes with an average of 68% in final grades and averages ranging from 69% (Pace 1 and Pace 4) to 75% (Pace 3) in pacing for earned scores at each of the progress check points. The failing CR case with a final grade of 58% shows extremely slow pacing, while the passed CR case with a final grade of 85% shows the fastest pacing. Particularly, in concert with the learning profile and intensive time investment in the first half of the academic term, the passed CR student's proportion of earned scores to the pacing guide standard approaches 180% at week 4 and week 8.

Other clusters including members to some degree show learning outcomes as follows: for Cluster 3 (n=35), 31% at week 4, 46% at week 8, 48% at week 11, 45% at week 15, and 67% at the final week; for Cluster 6 (n=6), 60% at week 4, 68% at week 8, 78% at week 11, 88% at week 15, and 92% at the final week; and for Cluster 7 (n=7), 120% at week 4, 105% at week 8, 97% at week 11, 107% at week 15, and 91% at the final week. Those clusters were not included in the scatter plot analysis because no CR member was assigned.

Spring Semester

For the 34 enrollment records including seven CR cases, data of time spent in the LMS was introduced to obtain data-driven clusters. Table 5 summarizes how those were grouped into five unique clusters.

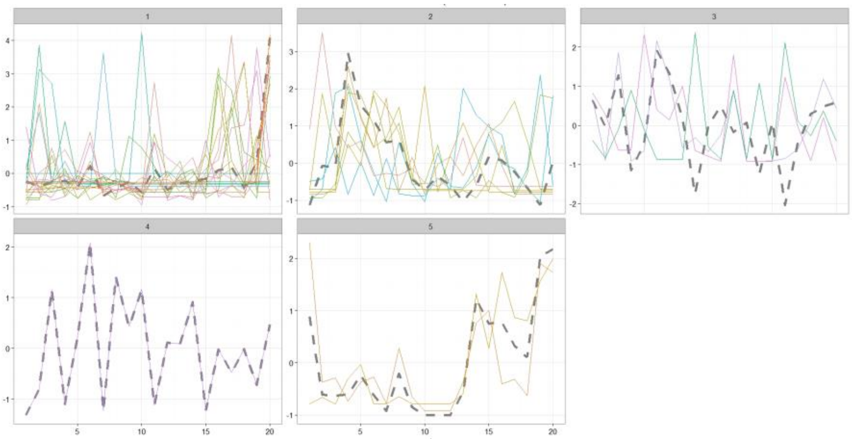
Table 5. Cluster Summary of Spring Semester (k=5)

Cluster	Size (#)	Size (%)	Failing (#)	Failing (%)	CR Case (#)	CR Case (%)	Passed CR (#)	Passed CR (%)
1	20	59%	6	67%	4	57%	3	60%
2	8	24%	3	33%	3	43%	2	40%
3	3	9%	--	--	--	--	--	--
4	1	3%	--	--	--	--	--	--
5	2	6%	--	--	--	--	--	--
Total	34	100%	9	100%	7	100%	5	100%

Cluster 1 is composed of various types of members in terms of CR status and course completion status. Of note, the percentage pertaining to failing members (67%) is slightly greater than the cluster size percentage (59%). Another cluster of various types of members is Cluster 2 and 33% of failing cases; 43% of CR cases were part of this learner group. Passed CR cases were divided into Clusters 1 and 2 with Cluster 1 including one more case. Out of 34 enrollments, 18% were assigned to one of three small-size clusters whose members were only from passed enrollment records.

Figure 5 presents the times series plot for each of the five clusters. Observing the trend over the 20 weeks informs when and how students invested their time in the coursework through the LMS.

Figure 5. Time Series Chart of Time Spent in LMS for Spring Semester (k=5)



Cluster 1 time series indicates a sharp peak at the final week suggesting a final spike profile, whereas Cluster 2 has a notable peak that is relatively broad, spanning over the first 10 weeks, implying their intensive time devotion to the coursework during the first half of the academic term. As a minority group of students in terms of success results, Cluster 3 and Cluster 4 are characterized by more frequent peaks, while Cluster 5 has the most significant peak in the first week and other sizable ones prior and subsequent to spring break.

Table 6 provides additional explanation by descriptive results to the profiles captured by time series plots.

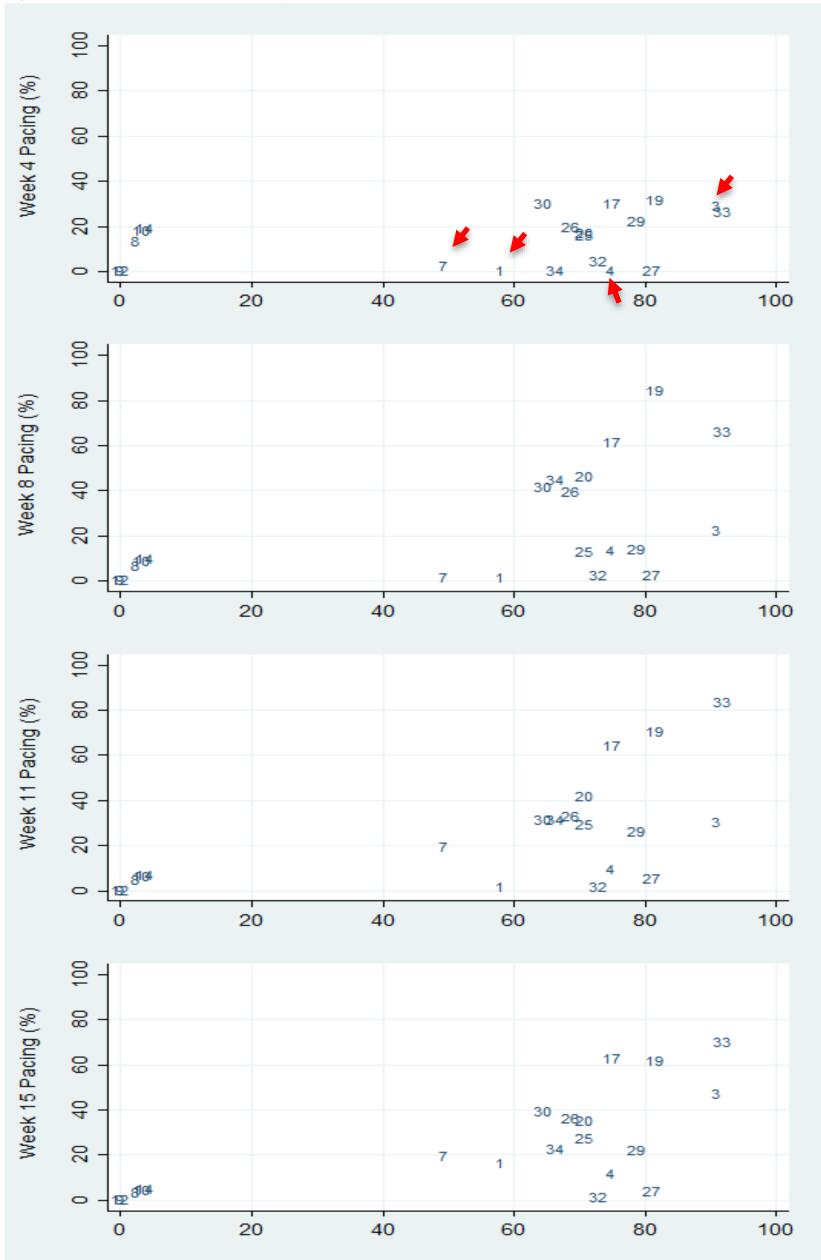
Table 6. Descriptive Summary of Time Spent in LMS for Spring Semester

Cluster	Avg. of Q1 Sum	Avg. of Q2 Sum	Avg. of Q3 Sum	Avg. of Q4 Sum
1	551	358	673	2,117
2	2,585	1,781	1,224	1,273
3	9,085	7,476	6,091	10,020
4	2,198	4,775	2,471	2,681
5	504	204	493	1,015

Cluster 1 members' average of total minutes for the final quarter (Q4=2,117) are between three and six times as great as those for its other quarters (Q3=673 and Q2=358). Cluster 2's profile of intensive time investment from the beginning of the course can be reaffirmed by having the highest average of total minutes for Q1.

Figure 6 and Figure 7 report learning outcomes of Cluster 1 and Cluster 2, both of which include CR enrollments as their members.

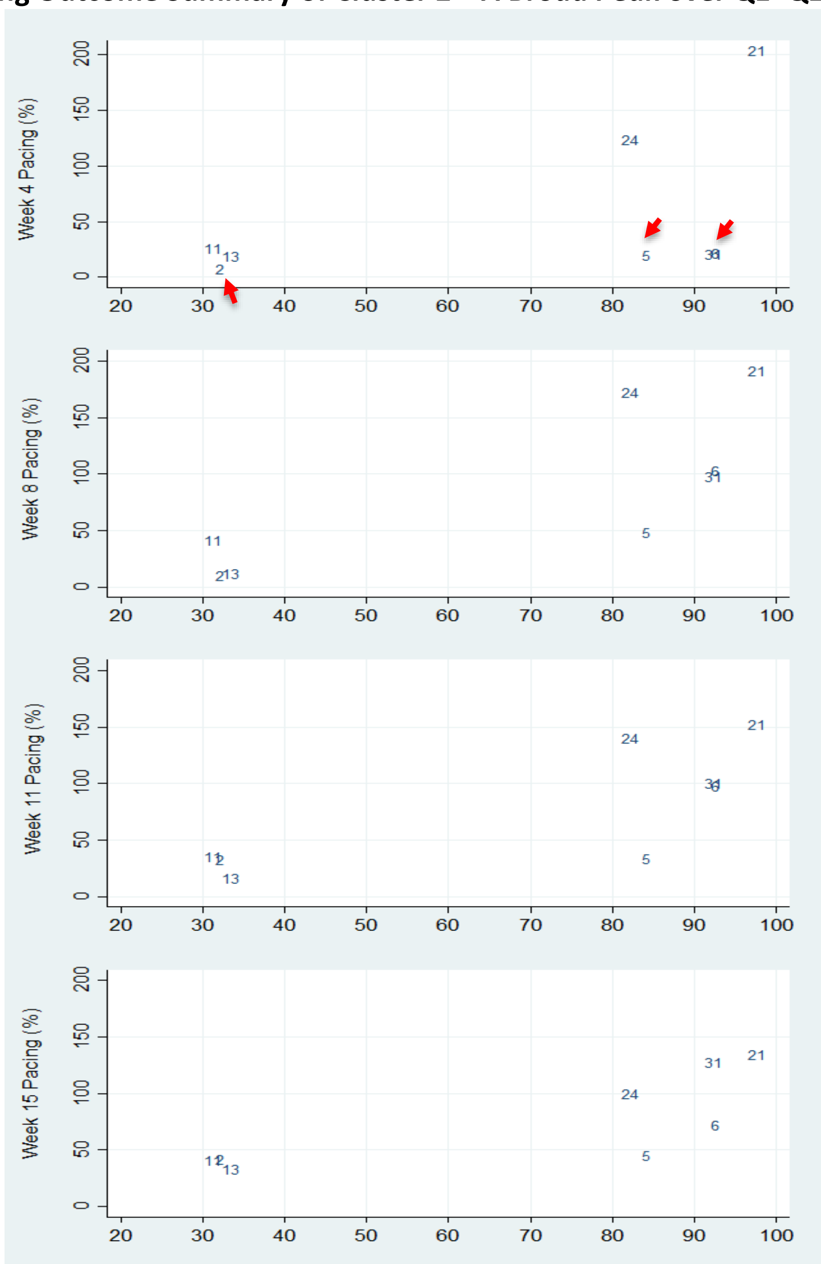
Figure 6. Learning Outcome Summary of Cluster 1-- A Peak at Final Week (k=5, CR=4)



Note. The CR case data points have been marked by 1, 3, 4, and 7.

Among the four CR cases that were assigned to Cluster 1, one failing case with a final score of 58% illustrates a learner who has intensive time investment for the final weeks and subsequently poor pacing throughout the semester. Notably, the CR case with a final score of 49% is the instance when the course was completed with an extension after the official final week. In addition, spring semester data indicates one more passed CR case with a final score of 75% having the profile of peaks at final term and overall poor pacing. The last CR case with a final score of 91% shows improved pacing with 29% at week 4, 22% at week 8, 30% at week 11, and 47% at week 15. Those results demonstrate that CR students may be unable to complete the course successfully within the given time period if they spent less time in the course and consequently maintained a pacing rate ranging from 0% to 2% until the semester was half-way over.

Figure 7. Learning Outcome Summary of Cluster 2 – *A Broad Peak over Q1~Q2* (k=5, CR=3)



Note: The CR case data points have been marked by 2, 5, and 6.

A signal of more improved pacing was found from Cluster 2 members as a result of intensive time investment in earlier stages. Of note, the vertical axis was rescaled to 0 from 200% to fit the data distribution. When compared with Cluster 1 members, several data points can be found in the upper-right region of the scatter plot, which represents the characteristics of high-achieving and fast-paced; specifically, two successful CR cases with an average of 84% and 92% in final scores appear to earn 47% and 102% of scores respectively, as suggested by the pacing guide by week 8. By contrast, the failing case with a final score of 32% has a pacing rate of 9% at week 8. These results suggest that some students, including CR, may not achieve such desired outcomes as fast pacing and consequently successful course completion, even after an intensive time investment in the first half of academic term.

Summer Semester

For the 91 summer enrollment records, including 23 CR cases, data of time spent in the LMS was introduced to obtain data-driven clusters. Table 7 reports the characteristics of generated learning profiles with the cluster number specified at five.

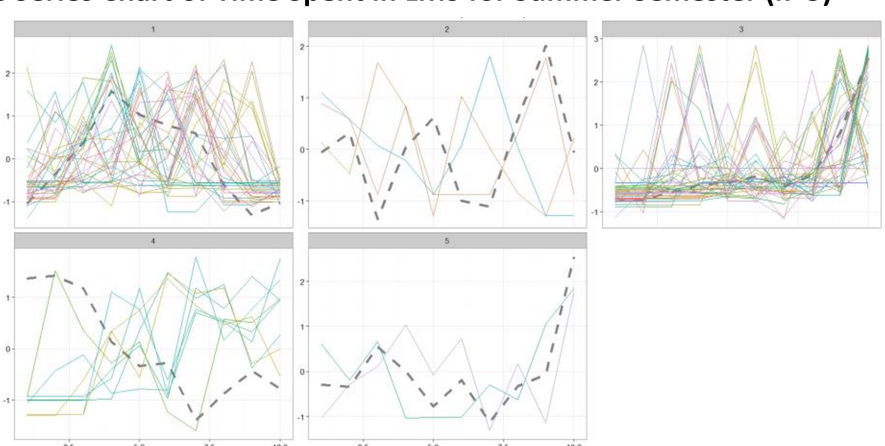
Table 7. Cluster Summary of Summer Semester (k=5)

Cluster	Size (#)	Size (%)	Failing (#)	Failing (%)	CR Case (#)	CR Case (%)	Passed CR (#)	Passed CR (%)
1	35	39%	6	25%	5	22%	3	21%
2	3	3%	1	4%	1	4%	--	--
3	43	47%	16	67%	13	57%	7	50%
4	8	9%	1	4%	4	17%	4	29%
5	2	2%	--	--	--	--	--	--
Total	91	100%	24	100%	23	100%	14	100%

The largest group is Cluster 3 with 47% of the summer sample, and in it, 67% of failing cases and 57% of CR cases assigned. The next largest group, with 39% of the summer sample, 25% of failing cases, and 22% of CR cases, is Cluster 1. Approximately 20% of CR enrollment cases appear to be part of Cluster 2 or Cluster 4; in particular, all of Cluster 4 CR members are from passed enrollments. Notably, the proportions that are related to CR cases (17%) or successful CR cases (29%) are greater than the proportions pertaining to cluster size (9%) or failing cases (4%)

Figure 8 presents the times series plot for each of the five clusters to observe the trend over the 20 weeks.

Figure 8. Time Series Chart of Time Spent in LMS for Summer Semester (k=5)



Cluster 3 demonstrates a profile of final peaks in time investment. Cluster 1 can be profiled as a broad peak over the second and third quarters of the 10-week summer term, as well as a noticeable downward trough implying less course engagement during the final couple of weeks for Cluster 1 members. Two smaller groups, Cluster 2 and Cluster 4 also include CR members. In particular, all CR members from Cluster 4 successfully completed the course, and their time series data can be construed as consistent time investment after a slow start based on a broad peak in the early weeks and small peaks after the midpoint of the summer term and also at the final weeks.

Table 8 provides additional explanation by descriptive results of the profiles captured by time series plots.

Table 8. Quarter Summary for Summer Semester

Cluster	Avg. of Q1 Sum[1]	Avg. of Q2 Sum	Avg. of Q3 Sum	Avg. of Q4 Sum
1	872	4,585	4,000	533
2	2,568	2,280	3,317	546
3	177	866	785	2,468
4	291	1,674	3,427	1,885
5	920	1,629	1,181	1,890

Note [1]: The 2-week interval was used to define Q1 (week 1 to week 2) and Q4 (week 9 to week 10), while the 3-week interval was used to define Q2 (week 3 to week 5) and Q3 (week 6 to week 8).

Given that Q4 was defined by a two-week interval while Q2 and Q3 were defined by a three-week interval for the summer data, it is notable that on average, across members, the total minutes spent over the two weeks (Q4) is greater than the total minutes over the three weeks (Q2 or Q3) for Cluster 3. In the middle six weeks of summer semester (Q2 and Q3), Cluster 1 shows the most intensive time investment when compared to other clusters.

Table 9 presents the clustering result for the 10 groups.

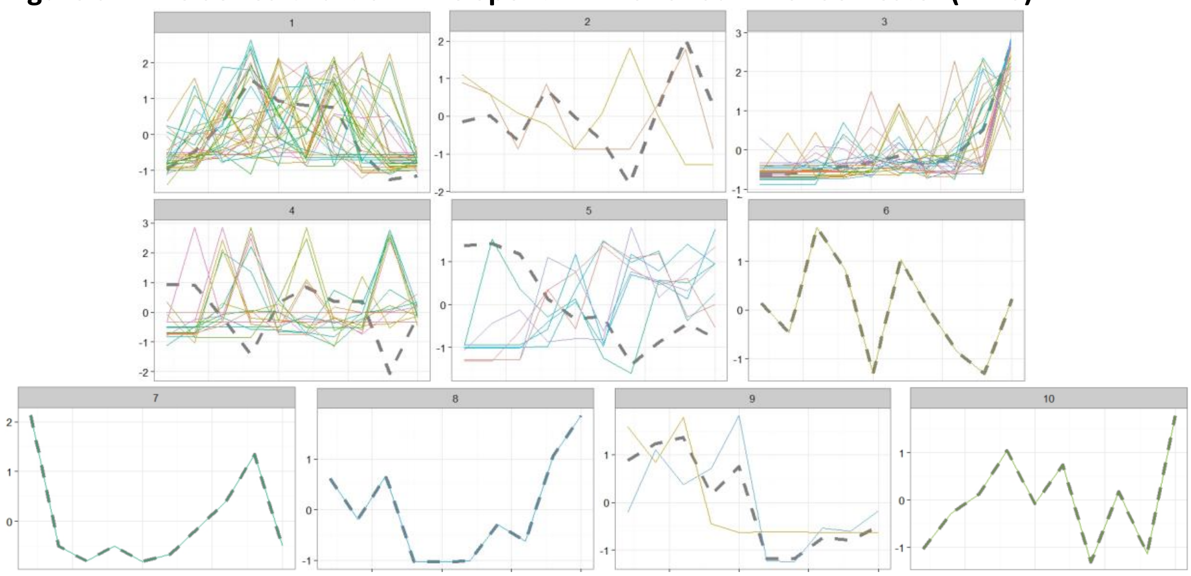
Table 9. Cluster Summary of Summer Semester (k=10)

Cluster	Size (#)	Size (%)	Failing (#)	Failing (%)	CR Case (#)	CR Case (%)	Passed CR (#)	Passed CR (%)
1	32	35%	6	25%	5	22%	3	21%
2	2	2%	1	4%	1	4%	--	--
3	25	27%	9	38%	7	30%	4	29%
4	18	20%	7	29%	6	26%	3	21%
5	8	9%	1	4%	4	17%	4	29%
6	1	1%	--	--	--	--	--	--
7	1	1%	--	--	--	--	--	--
8	1	1%	--	--	--	--	--	--
9	2	2%	--	--	--	--	--	--
10	1	1%	--	--	--	--	--	--
Total	91	100%	24	100%	23		14	

The largest cluster, Cluster 1, has 35% of summer sample members and a slightly low level of percentages pertaining to failing (25%) and to CR (22%) enrollments. Of the five CR members, 3 cases were from passing enrollments. The second largest group is Cluster 3 (27%), which contained 38% of the failing cases, 30% of the CR cases, and 29% of the passing CR cases. Of note, all four of the CR enrollments within Cluster 5 passed.

Figure 9 depicts trend patterns of summer enrollments' time investment in the course through the LMS over the 10 weeks.

Figure 9. Time Series Chart of Time Spent in LMS for Summer Semester (k=10)



The largest group, Cluster 1, can be characterized as a broad peak over the second and third quarters of the 10-week summer term, whereas Cluster 3 shows patterns of procrastinated learning where time investment rises significantly in the final weeks of the course. Two broad peaks in the beginning and the middle of the course stand out from the Cluster 4 trend patterns. Unlike other clusters, Cluster 5 can be better characterized by downward troughs, not by peaks; one occurs in Q2 period (i.e., weeks 3 to 5) and the other ranges from week 8 to week 9, suggesting during those time periods, there was a decrease in the strength of peak, from such situations as a smaller number of members showing a peak, a smaller degree of individual members' peaks than previous time points, and/or individual members' gradual decrease in the data.

Table 10 presents members' averages of total minutes in the LMS during the first two weeks (Q1), the next three weeks (Q2), the following three weeks (Q3), and the final two weeks (Q4).

Table 10. Quarter Summary for Summer Semester

Cluster	Avg. of Q1 Sum[1]	Avg. of Q2 Sum	Avg. of Q3 Sum	Avg. of Q4 Sum
1	760	4,810	4,300	475
2	3,282	2,132	3,940	435
3	194	420	834	3,079
4	154	1,485	715	1,619
5	291	1,674	3,427	1,885
6	1,141	2,576	2,071	769

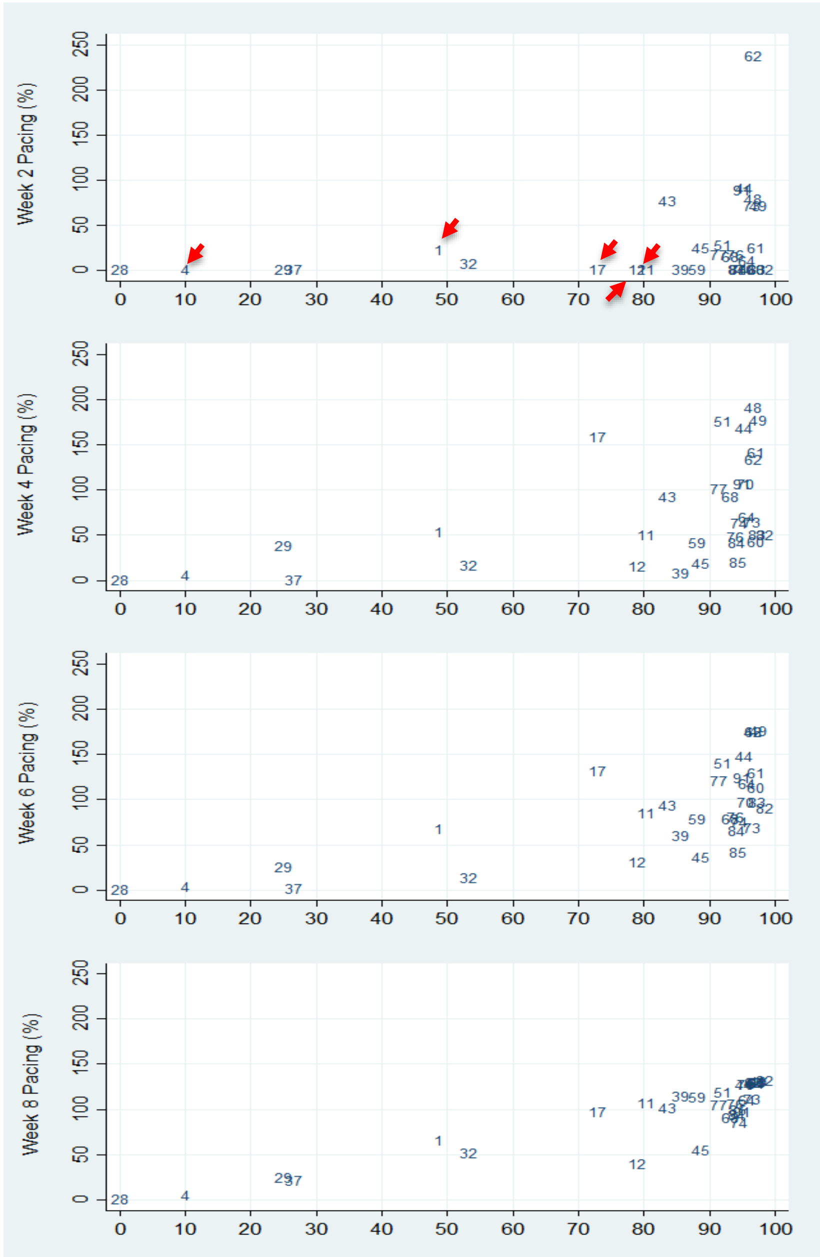
Cluster	Avg. of Q1 Sum[1]	Avg. of Q2 Sum	Avg. of Q3 Sum	Avg. of Q4 Sum
7	2,624	518	1,811	2,037
8	1,063	729	494	2,129
9	1,796	3,025	296	707
10	777	2,529	1,869	1,650

Note [1]: The 2-week interval was used to define Q1 (week 1 to week 2) and Q4 (week 9 to week 10), while the 3-week interval was used to define Q2 (week 3 to week 5) and Q3 (week 6 to week 8).

Averages of the total minutes for the particular time segments across members provide further explanation on profiles captured by time series plots. For instance, Cluster 1 shows relatively higher averages at Q2, which also correspond to the broad peak over the second and third quarters of the summer semester. Also, the sharp rise from Q3 to Q4 can be found from the final spike group, Cluster 3. Noticeable time investments appear to occur at Q2 and Q4 for Cluster 4 and at Q2 through Q4 for Cluster 5.

Finally, learning outcomes were explored for Cluster 1, Cluster 3, Cluster 4, and Cluster 5 when the number of clusters was specified at 10. In the summer semester, progress was monitored every other week, thus Figure 10 through Figure 13 are scatter plots of the proportion of earned scores to the scores suggested by the pacing guide at those checkpoints against the final scores.

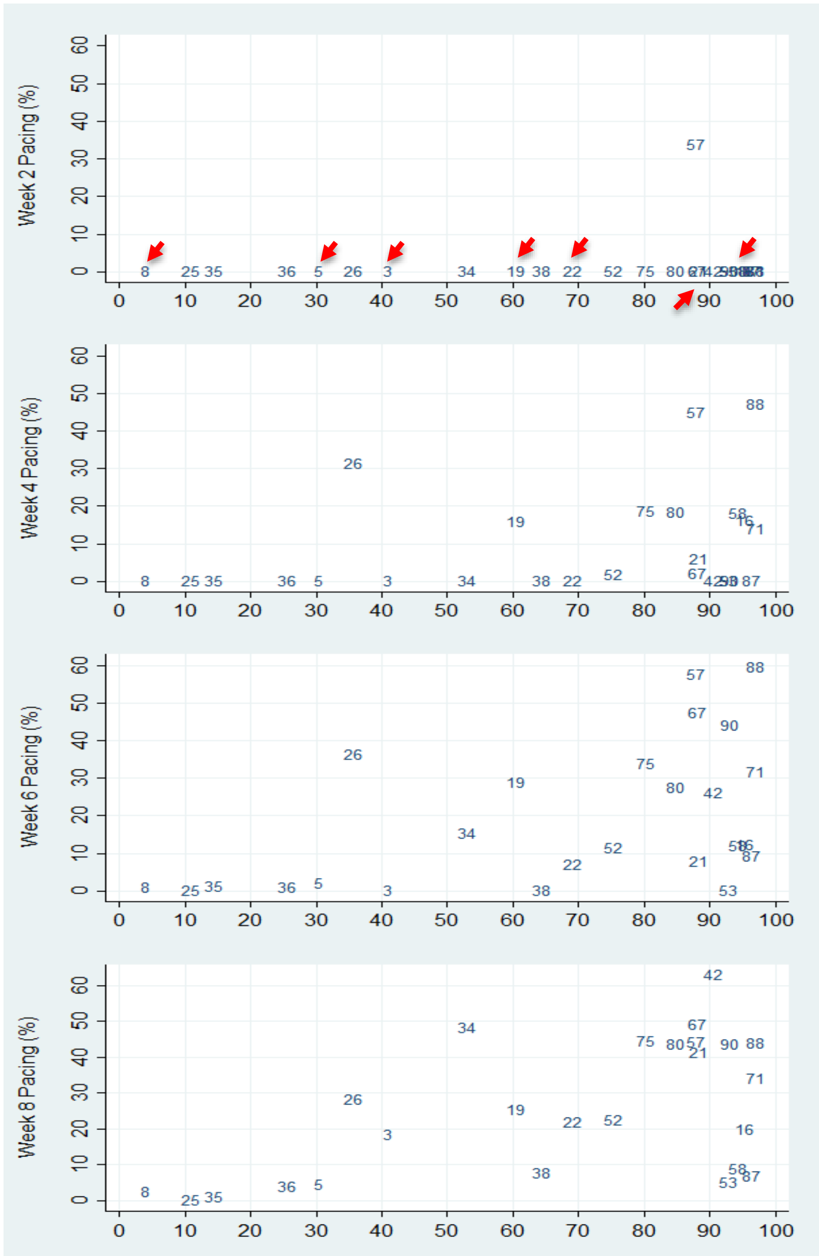
Figure 10. Learning Outcome Summary of Cluster 1 – *A Broad Peak over Q2~Q3* (k=10, CR=5)



Note: The CR case data points have been marked by 1, 4, 12, 17 at a final score of 79%, and 11 at final scores of 80%.

Cluster 1 members show a gradual improvement in pacing, with 27% at week 2, 73% at week 4, 85% at week 6, 92% at week 8, and 80% at the final week, as a result of consistently devoting a great deal of time to the course over the mid time period of 6 weeks. Two CR cases with 73% and 80% as final scores appear to conform to those profiles in terms of learning behavior patterns and learning outcomes. Two CR cases with 48% and 79% as final scores share similar patterns in terms of time investment on the time series, but the failing case shows better pacing throughout the time period. The observation of case-level data found that the failing CR case's time investment during the latter half of the 10 weeks was much less than the cluster members' average, leading to course failure despite the early time investments. The last case, with a 10% final score, could be assigned to Cluster 1 based on data distributions on the time series, but overall, the measured values appear to be much less than the cluster members' average.

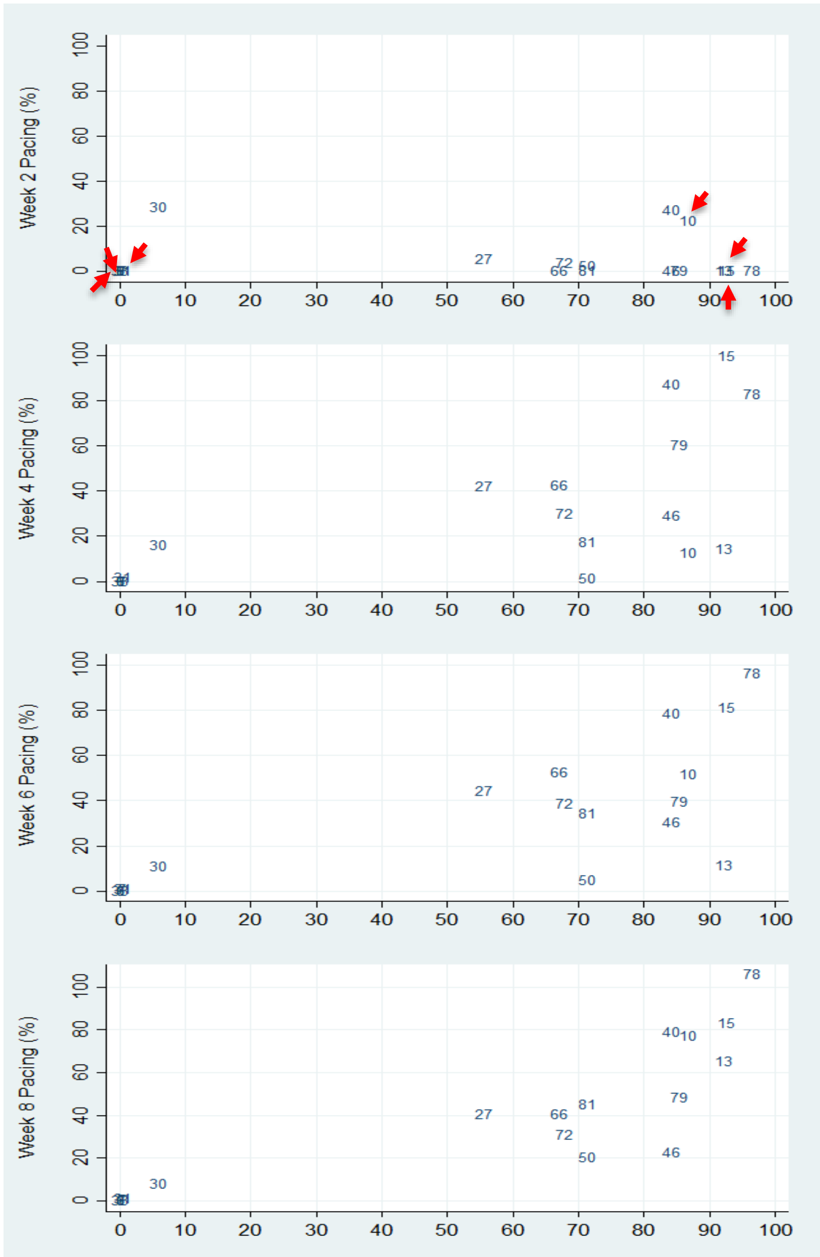
Figure 11. Learning Outcome Summary of Cluster 3 – *A Sharp Peak in Final* (k=10, CR=7)



Note. The CR case data points have been marked by 3, 5, 8, 19, 22, 21 at final score of 88%, and 16 at final scores of 95%.

Cluster 3 members' average of pacing-related scores are 1% at week 2, 9% at week 4, 19% at week 6, 25% at week 8, and 67% at the final week, as a result of investing time heavily during the final couple of weeks. The two passing CR cases, with final scores of 95% and 61%, show pacing above the cluster average at or after week 4, while the other two passed CR cases, with 69% and 88% final scores, can be characterized by a surging increase in pacing-related outcome from the third check point to the fourth check point. None of the three failing CR cases' proportions of earned scores to pacing guide standards exceeded the cluster averages.

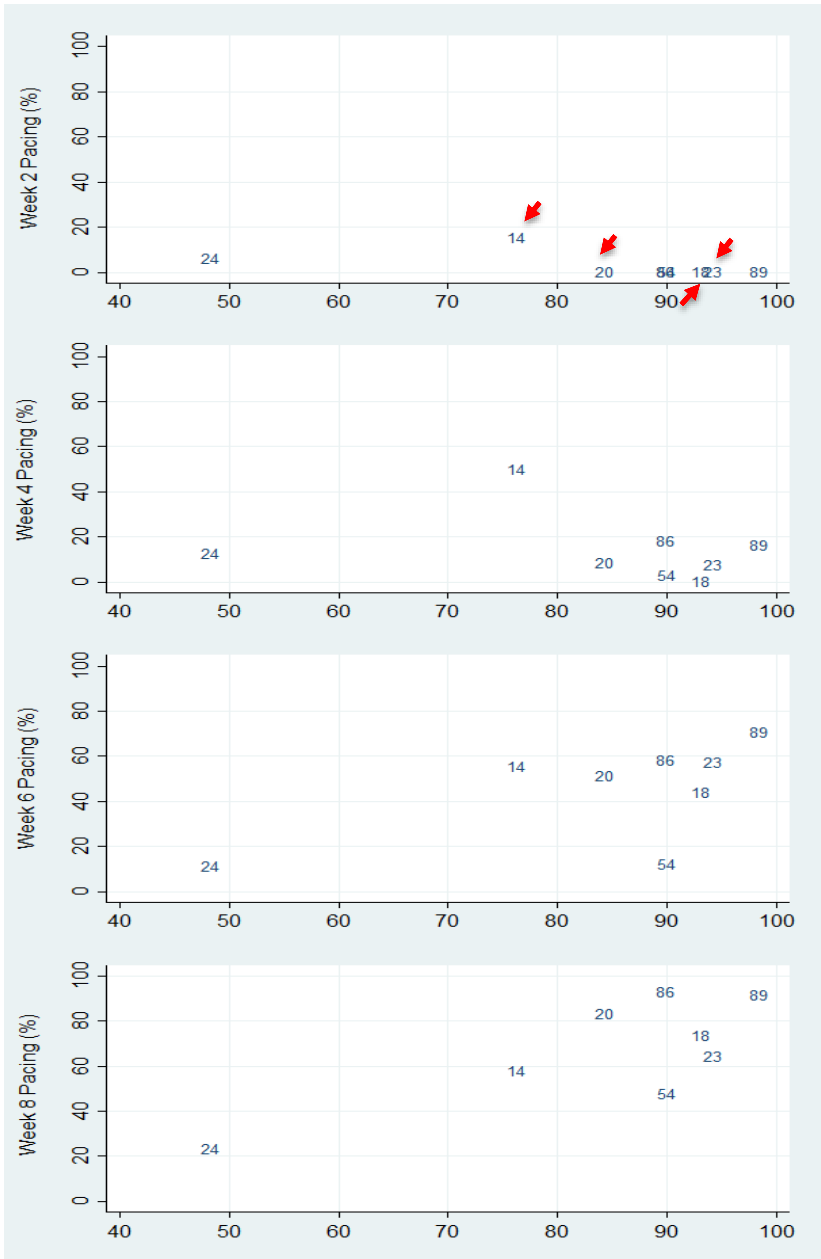
Figure 12. Learning Outcome Summary of Cluster 4 – *Peaks in Q3 and Q4* (k=10, CR=6)



Note: The CR case data points have been marked by six at final score of 0%, nine at final score of 0%, seven at final score of 4%, 10 and 13 at final score of 92%, and 15 at final score of 92%.

The clustering analysis algorithm regarded three CR cases that could be construed as "de facto dropping out of course" as the time series patterns of Cluster 4. See the three data points at final score of 0% on the scatter plot. After removing those cases, members appear to score 7% at week 2, 41% at week 4, 44% at week 6, 51% at week 8, and 74% at the final week. Three passed CR cases with final scores of 87%, 92%, and 92% share the cluster's learning profile of intensive time investments prior to and during the final weeks, leading to the proportion of earned scores to scores suggested by the pacing guide at week 8 and appearing to exceed 60%.

Figure 13. Learning Outcome Summary of Cluster 5 – *Peaks and Small Final Peak* (k=10, CR=4)



Note: The CR case data points have been marked by 4, 20, and 18 at a final score of 93%, and 23 at a final score of 94%.

Finally, the group with intensive time investments after a slow start – most of the Cluster 5 members, including four CR cases (76%, 84%, 93%, and 94% final scores) – show pacing percentages greater than or approximately equal to 50% from the third progress check point, and the member averages are 3% at week 2, 14% at week 4, 45% at week 6, 66% at week 8, and 84% at the final week.

Discussion

Two 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. The current report presented results in which the variable of time-in-LMS was used. Observing clustering results revealed that the majority of students showed an intensive time investment during the final weeks, whereas a small minority of students showed multiple occurrences of intensive time investment over academic terms of either 10 or 20 weeks. Although the foregoing statement was true for CR cases, particularly from the spring and summer results, they were also often members of the groups profiled as having no peaks in the final weeks or early course work time investments when the semester started. A discussion of those findings, in light of literature on academic time, will explain any new understanding of learners in virtual courses, including at-risk students, and will inform us how to better serve them.

There is a long tradition of acknowledging the importance of time factors in understanding the learning process and its relationship with learning outcomes. For example, classic works of Carroll (1963) and Fisher and colleagues (1980) formed the foundation for the validity of increasing students' learning time. In this respect, there is empirical evidence within the online learning context; Liu and Cavanaugh (2011) found that the variable of time that students spent in the LMS was a significant success factor in mathematics and social studies courses.

The present study suggests a new approach to the problem of academic learning time in the context of online learning, namely that an increase in the time students spend in the LMS for specific time segments, for instance during either the early weeks or the final weeks of the semester, is not necessarily linked to success in the course. Specifically, fall semester data generated 10 clusters (i.e., k=10) and, for the early time investment groups, the percentage of failing cases was greater than the percentage pertaining to cluster size (cluster 2: cluster size = 13% vs. failing case size = 21%) and the final spike (cluster 3: cluster size = 49% vs. failing case size = 64%).

Spring semester results indicated that the CR students were again assigned to one of the two clusters whose members invested time at either the beginning or the end of the semester. It was also found that some students, including CR students, could not achieve such desired outcomes as fast pacing and subsequent successful course completion, even after an intensive time investment in the first half of the academic term. Therefore, it would be more desirable to guide students to employ methods in which the aggregate academic learning time is increased by frequent occurrences of intensive time investment throughout the semester rather than by much more intensive time investment during particular time sections.

Summer results highlight another practical implication specifically impacting CR cases. During this short academic term, most failing CR members showed time records that were well below their cluster averages. With regard to Cluster 1, whose members showed multiple peaks during the second and third quarters of the term and did not resort to a final spike, the two failing CR members' time records (the quarterly sum of minutes) ranged from 0 to 559 for the first quarter, 103 to 3,141 for the second quarter, 207 to 1,221 for the third quarter, and 12 to 101 for the final quarter, which were less than the cluster averages of 872; 4,585; 4,000; and 533, respectively. In contrast, the three passed CR members were more likely to exceed the cluster averages for at least one quarter. Of the six failing CR students assigned to Cluster 3, where the sharp peak during the final weeks stood out, five had time records ranging from 0 to 0 for the first quarter, 0 to 624 for the second quarter, 0 to 207 for the third quarter, and 0 to 551 for the final quarter. These time records were below the cluster averages (177, 866, 785, and 2,468). Of the seven passed CR students, five students' records exceeded the cluster averages for at least one quarter. These results highlight the importance of mentoring students' coursework during the summer semester.

As we cannot always equate time-in-LMS with time-on-task, the present study's findings need to be discussed in light of a study by Kovanovic´ and his colleagues (2015). The authors pointed out that there were challenges with the research on academic time variables captured by the LMS trace data, in particular their inaccuracy as an estimation of academic learning time, and found that a substantial proportion of variance in course outcomes was attributable to the choice of approach to time-on-task estimation. Note that this study's data source is Moodle trace records from the 13-week-long graduate level course. Specifically, LMS data is stored in the form of timestamps of user's particular activities, and thus academic learning time should be calculated by the difference from the start time of a particular activity to the start time of the subsequent activity. However, data often contain outliers with exceptionally long time periods and duplicate log-ins after prolonged time periods within the same session.

In order to address those challenges, researchers in the field of learning analytics or educational data mining often adopt specific strategies, such as estimating the duration of last action (e.g., average of all last action times for individual students) or replacing those outliers with a particular threshold value. According to the authors' modeling results, ignoring those data inaccuracies (i.e., no outliers or last action processing) resulted in poorer model estimation than adopting special strategies in predicting various learning outcomes, including literature review score, journal reading score, participation grade, and final percentage grade. Even a simple strategy in which outliers were not specially processed but last action records were removed from the time-on-task estimation improved model estimation for such outcomes as journal readings or higher cognitive presence levels (Kovanovic´ et al., 2015). Although the current study is relatively free from this matter because of its focus on patterns in academic learning time rather than the aggregate amount of time, including data processes for more accurate time-on-task estimation must be potential areas for future work.

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Appendix

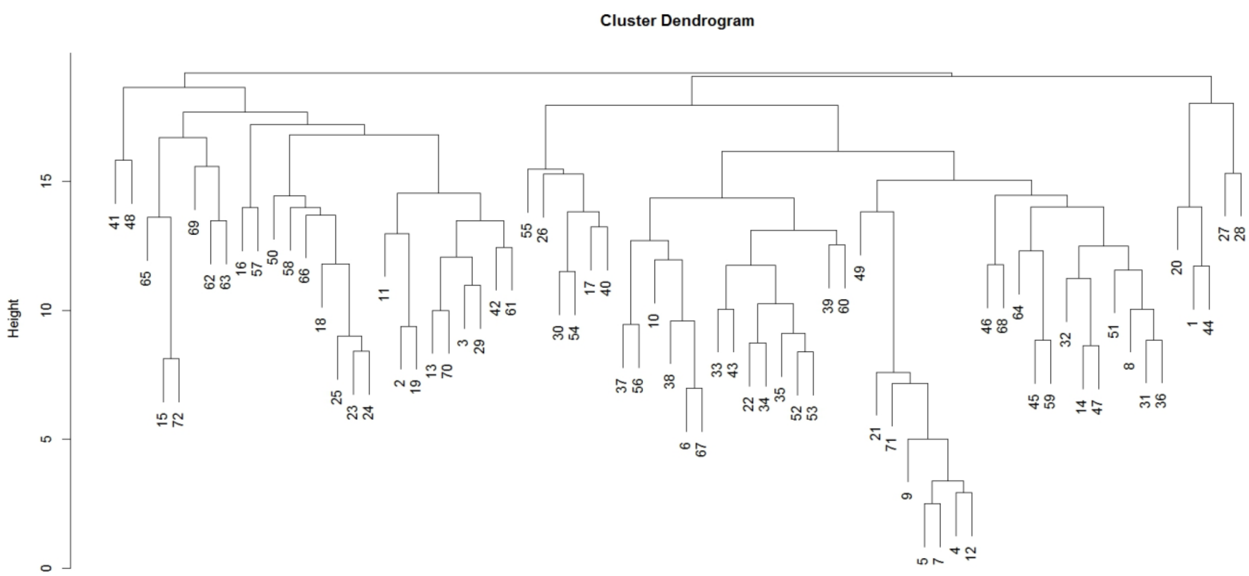
From the fall semester data, special cases and their coding numbers included two cases for failing credit recovery enrollments (coded #1 and #2 in the time series data), one case for the passing credit recovery enrollments (coded #3), and 12 additional failing cases having reasons other than CR (coded #4 through #15).

From the spring semester, special cases and their coding numbers included two cases for the failing CR (coded #1 and #2 in the time series), five cases for the passing CR (coded #3 through 7), and seven additional failing cases having reasons other than CR (coded #8 through #14). With a slight revision of the gradebook, the full possible score was 1,370, and the passing mark was 822.

In the summer semester data, special cases included nine failing (coded #1 through #9), 14 passing CR cases (coded #10 through 23), and an additional 15 failing non-CR cases (coded #24 through #38). The CR cases totaled 23, and the failing cases totaled 24. The possible course score was 1,370, and the passing mark was 822.

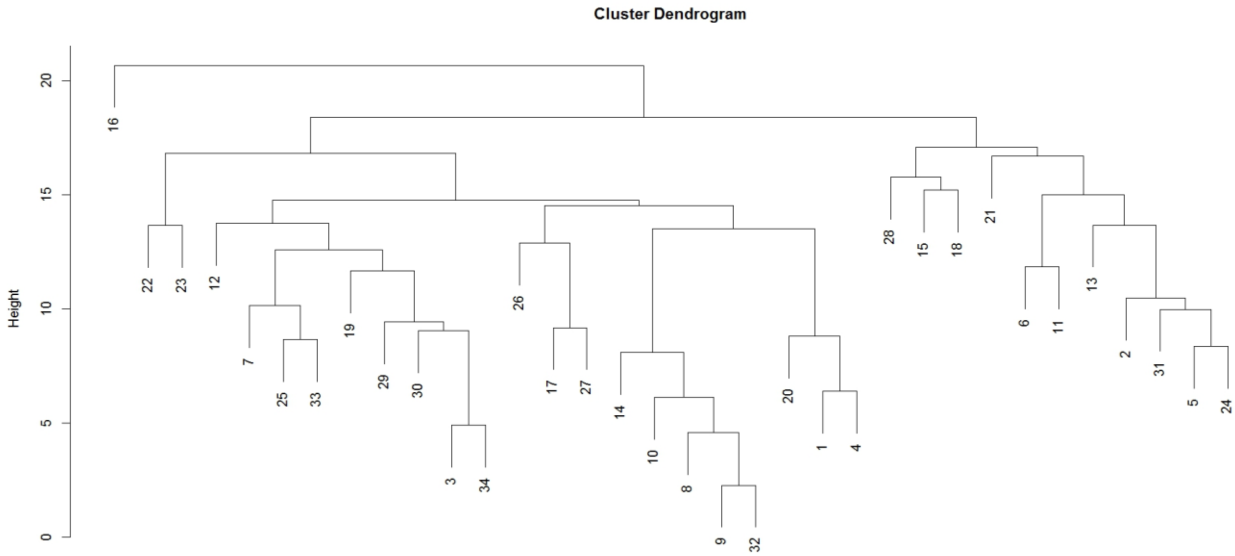
Dendrogram of Time Spent in LMS

Fall



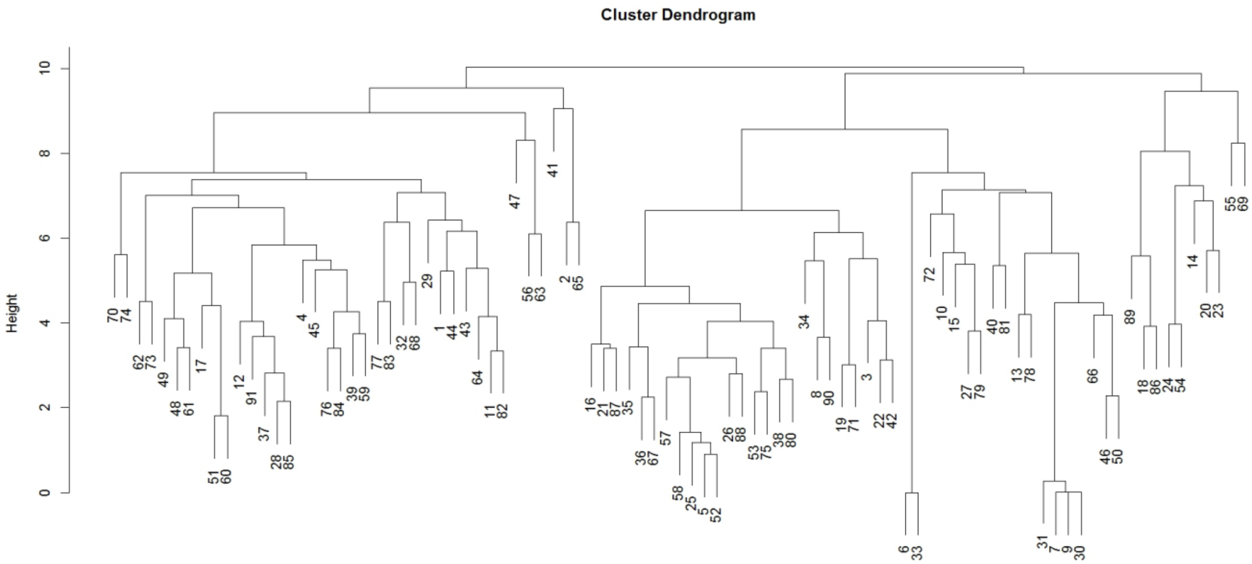
#1 ~ #2: Failing CR#3: Passing CR#4 ~ #15: Failing Non-CR (n= 72)

Spring



#1~#2: Failing CR#3~#7: Passing CR#8~#14: Failing Non-CR (n= 34)

Summer



#1 ~ #9: Failing CR-- #10 ~ #23: Passing CR-- #24 ~ #38 Failing Non-CR (n= 91)

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