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A Snapshot of Successful K-12 Online Learning: Focused on the 2015-16 Academic Year in Michigan

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The purpose of this study was to provide a snapshot of successful K-12 online learning in one of the frontrunner states in the field—Michigan. The authors explored the state's legislative and policy infrastructure; the beliefs, perceptions, and values of various stakeholders; and statewide enrollment patterns and effectiveness for the 2015-16 academic year. With that understanding, the study presented a secondary analysis of student information, activity, and performance data in a learning management system (LMS) in an attempt to explore success factors at the micro-level. The study results revealed the following: (a) the engagement pattern representing students' consistent and persistent attempts to complete course tasks week-by-week was the most powerful success factor; (b) a more nuanced notion of students' time spent in the LMS; and (c) a student population who presents unique needs to be successful in the online learning. The paper concludes with discussion about all findings in terms of a way of creating a feedback loop for upper-level systems.

Keywords: K-12 online education; student engagement in online learning; online learning success

INTRODUCTION

The K-12 online education field has seen a lot of growth since it began in the mid-1990s. For the 2015-16 academic year that was targeted in the present study, the number of course enrollments in the United States reached almost 950,000 (Evergreen Education Group, 2016). This growth was achieved by more than two decades of effort to provide access to online learning opportunities. While the potential benefits are enormous for improving educational outcomes, the K-12 online learning does not automatically guarantee its success simply by providing online learning opportunities (Barbour and Reeves, 2009). Now, the field's pressing question is how to provide access to *successful* online learning opportunities. One way to address that issue is by exploring student learning behaviors that are predictive of outcomes in online courses (e.g., Hung, Hsu, & Rice, 2012; Liu & Cavanaugh, 2011). This study is in line with previous studies to understand the characteristics of behaviors that relate to successful or failing course outcomes via analyzing learning management system (LMS) data.

In conducting the study, the authors, however, did not limit the scope of inquiry to only analyzing LMS data and discussing results within the selected models. Rather, the study adopted a holistic perspective, which enabled it to look inclusively and deeply at forces acting on students' success in online learning environments. Under the assumption that multiple systems affect students' success in school, certain educational programs, and life (Bronfenbrenner, 1977), the present study began by investigating upper-level systems, including policy and legislative infrastructure, public awareness of K-12 online education, school- and/or teacher-level contexts, and growth trends. Furthermore, the study team held a viewpoint that a policy did not always define policy parameters precisely, and thus continuous probing into factors that could increase the specificity was required in order to make the policy message clearer (Porter, Floden, Freeman, Schmidt, & Schwille, 1988; Porter, 1994). Therefore, the purpose of this study was to examine success or failing factors captured by student-level data that could help us create a feedback loop for upper-level systems such as informing policy.

Michigan provided an especially interesting context for the study. Following closely behind such early groundbreakers as Virtual High School and Florida Virtual High School, Michigan Virtual School (MVS) was established in 2000 and has grown to be one of the largest state virtual schools in the United States (Watson & Murin, 2014). In particular, by establishing a research institute funded by the Michigan legislature, Michigan has well documented policy and public structure around K-12 online learning. Furthermore, the institute has helped MVS to become one of the state virtual schools whose LMS data has been constantly examined using various analytic approaches (e.g., Lowes & Lin, 2017). Michigan accordingly enabled the authors to observe both upper-level systems and students' learning behaviors more efficiently than other states that lack resources to access and analyze LMS data on a large scale.

In the next section, the K-12 online education context in Michigan will be examined. Specifically, this study will describe the policy and legislative infrastructure, public perceptions, and issues related to online course access. In connection with that understanding, the paper will discuss findings from examining LMS data, focusing on how learning profiles were formed in online courses.

State Legislature and Policy System

There have been a number of successive statewide initiatives to support K-12 online learning in Michigan. In 2006, the legislature introduced a graduation requirement to the Michigan Merit Curriculum that students have an online learning experience, the first legislation of its kind in the nation (Michigan Public Act § No.123, 2006). This online learning experience does not require a fully-online, semester-length course; rather, it is described as "a structured learning activity that utilizes technology with intranet/internet-based tools and resources as the delivery method for instruction, research, assessment, and communication" (Michigan Merit Curriculum Guidelines, 2006, p. 1). Given the broad scope, students are able to fulfill this requirement through an online course, an online learning experience, or online learning incorporated into the required credits. Following the requirement, Michigan passed legislation to allow two full-time charter schools to operate statewide and, in 2012, raised the enrollment cap to allow up to 2% of Michigan's K-12 students to enroll in these schools (Michigan Public Act § No. 129, 2012).

In 2013 the Michigan legislature built on the original 2006 requirement by expanding access to online learning through Section 21f of the State School Aid Act (Michigan Public Act § No. 60, 2013). Section 21f allows students in grades 6-12 to take up to two online courses per academic term as requested by the student and paid for by the student's enrolled brick-and-mortar school. Certain criteria must be met for a student to enroll, mostly pertaining to the enrollment being in the best interest of the student and his/her educational path. There are also reasons why a district may deny an online enrollment, such as the student has already failed two online enrollments or the course is not capable of earning credit toward graduation; however, when an online course request is denied, a specific reason, based on what is listed in the legislation, must be provided to the student and parent.

Section 21f also makes provisions for districts interested in offering online courses to students within and outside of their district. Among these requirements is that a course syllabus is provided for inclusion in Michigan's Online Course Catalog ("Michigan's Online Course Catalog," n.d.).

Additionally, providers are required to add enrollment counts and pass rates (students who earn 60% or more of the total course points) for the previous year. This provision was added after the initial legislation in 2013 as a way to increase transparency for students and parents when "shopping" the course catalog.

The 2006, 2012, and 2013 legislation do not directly address student success in online learning as much as they expand options for K-12 students to pursue online learning in Michigan. We, however, found provisions in place to help ensure a base level of quality for K-12 online courses from the official definition of an online course in Public Act 249 of the State School Aid Act (Michigan Public Act § No. 249, 2016). An important emphasis in the definition is the requirement that the teacher of any online course holds a valid Michigan teaching certificate or permit recognized by the Michigan Department of Education (MDE). This means that while the students may be separated from their teacher physically, they still have a Michigan certified teacher leading the course. In addition to a Michigan certified teacher, current Michigan legislation requires that students have an on-site mentor, "a professional employee of the primary district who monitors the pupil's progress, ensures the pupil has access to needed technology, is available for assistance, and ensures access to the teacher of record" (p. 99), assigned to them by their primary school. Accordingly, in all cases a school must provide a mentor to students enrolled in an online course, and that mentor must be a professional employee of the school. Notably, the legislation does not make any requirements about the number of mentees assigned to mentors, set a minimum number or duration of interactions, or specify that the mentor has any teaching or related experience.

While Michigan has legislative provisions expanding access to K-12 online learning, and has provided *some* legislation to support student success, those efforts seem to be increasing public awareness to a more modest extent, rendering many students and parents unaware of their options in regard to online learning. In the *Public Awareness and Views of K-12 Online Learning in Michigan* report (Public Sector Consultants, 2017), when approximately 800 general public participants (Michigan Virtual Learning Research Institute, 2017) were asked in a 2016 survey whether that graduation requirement was true or false, 22% said it was true while 35% said it was false, and another 43% reported that they did not know. Regarding the requirement for an on-site mentor, 43% indicated they thought it was true, while 13% believed it was false. Another 47% of respondents were unable to answer the question. In this context, as part of a consumer awareness effort, Michigan developed and released *Consumer Awareness* (n.d.), which is an online resource, updated yearly, designed to inform parents, school personnel, school board members, and other constituents of the nature of online learning options, their effectiveness for Michigan students, the cost of these programs, and current trends in research, practice, and policy.

The field's growth resulting from extensive efforts made to increase access to online learning through policy and legislation in the state has been well evidenced in the annual publication, *Michigan's K-12 Virtual Learning Effectiveness Report* (Freidhoff, 2017). In the next section, the authors present a brief review of 2015-16 academic year's report.

Michigan's Status Quo in the 2015-16 Academic Year

The report analyzing Michigan students' online course enrollment and completion data has been released annually since the 2012-13 academic year. According to the report covering the 2015-16 academic year, 6% of Michigan public school students took at least one online course, and 87% of those online learners were in high school. The majority of online enrollments were in the four core subject areas of English language and literature, social science and history, mathematics, and life and physical Sciences, each accounting for between 17% and 20% of total online course enrollments.

With regard to school settings, the 2015-16 report stated that 63% of Michigan's school districts had online course enrollments in their schools. Some 88% of school buildings with online learners were classified as belonging to Local Education Agencies (LEAs), though LEAs accounted for only 54% of the state's total online course enrollments. Another entity type, Public School Academies (PSAs), commonly known as cyber charter schools, contributed an additional 44% of enrollments. Approximately half of Michigan's 1,026 schools reported 100 or more online enrollments each; but notably, the 44 schools flagged as providing full-time virtual curricula for their students were responsible for 37% of all online enrollments.

As a source of evidence for success factors in online learning, the 2015-16 report found evidence of success and also areas that needed improvement. It did not advance any explanations of why course pass rates varied so widely across entity types: for instance, relatively few students in LEAs had a pass rate of 65%, whereas a much larger number in PSAs had a pass rate of just 51%, far short of the study sample's overall pass rate of 58%. Locale-coded records revealed similar patterns: residential categories with high proportions of overall online enrollment were associated with lower pass rates, for example, "Suburb" (enrollment proportion=28%, pass rate=61%) and "City" (enrollment proportion=24%, pass rate=50%) vs. "Rural" (enrollment proportion=14%, pass rate=64%) and "Town" (enrollment proportion=9%, pass rate=70%). Greater heterogeneity in data subsets with larger numbers of enrollments could explain this phenomenon. It might also reflect a lack of empirical evidence on which to base judgments about the effectiveness of growth of online enrollments on a large scale, and about the effectiveness of such learning in a more general sense; however, such considerations are beyond the scope of this study.

Viewed through the prism of success factors, one data subset that followed the aforementioned pattern was the enrollment records of MVS (for a detailed description, see the Study Site subsection of the Methods section, below). Specifically, the MVS subset, which accounted for only 4% of the state's total online enrollments in 2015-16, had the highest pass rate (81%) among all subsets. Notably, MVS's online learners were more likely to be successful in other environments as well. Among enrollment records that contained performance information from a minimum of three non-virtual courses, two-thirds of MVS students had passed all of their non-virtual courses. Conversely, the percentages of students in other subsets whose records were marked "not passed three or more non-virtual courses" were, on average, three times higher than at MVS.

Despite these characteristics unique to MVS, it may be a good starting point for exploring online learning success factors at the student level, for two reasons. First, MVS's high proportion of previously successful learners could simply reflect the effectiveness of its efforts to promote, market, and position itself as a provider of online learning opportunities in conjunction with traditional schools—where these students are already excelling; this could have boosted MVS's capacity to attract students who were more motivated and self-directed, and thus more successful, regardless of course format. If so, fine-grained analyses of those learners' behaviors in their courses likely would provide considerable insight into how students succeed in online learning. Second, after taking into account their non-virtual performance on state level assessments, MVS students outperformed students enrolled with other virtual course providers in English, mathematics, science, and social studies (Freidhoff, 2017).

Student Learning Behaviors and Outcomes in Online Courses

In examining online learning success at the student behavior level, prior researchers have commonly used two key login variables—frequency and duration. For example, Liu and Cavanaugh (2011) analyzed LMS data from a state-level virtual high school and reported that there was a negative association between the number of logins and final grades in three out of 15 courses. All three of the courses in question were in mathematics. However, algebra and geometry were among the 11 courses in the same study where login duration was positively correlated with grades. The authors suggested a possible interpretation that having sustained time on task would be more beneficial to achievement than having frequent but short time on task. Yet, they emphasized that future studies needed to go beyond the aggregate variables and thus take the distribution of login frequencies throughout the semester into account.

Hung, Hsu, and Rice (2012) included behavioral indicators from a wider variety of courses offered by a state-wide K-12 online institution. Their study revealed that, in general, the more actively students engaged with course materials, the better their course grades. However, it is worth noting that all the behavioral indicators of engagement level took the form of frequency, such as numbers of clicks and discussion-board entries, and how often course content, pages, tabs, and modules were accessed. Those measurement methods should be borne in mind when considering one of Hung, Hsu, and Rice's counterintuitive findings: that students in mathematics and science courses who actively engaged with course materials performed less well than their equally engaged counterparts in other subject areas. Although the authors suggested a plausible explanation from the perspective of course design features, this study also reiterates that many unanswered questions remain regarding the role of engagement variables and/or the use of frequency-based indicators in predicting online learning success.

A more recent study by Pazzaglia, Clements, Lavigne, and Stafford (2016) is especially interesting in this context. Instead of aggregate variables, the study used time-series data (i.e., weekly login duration) from 109 courses across a 21-week semester at a virtual school. The method was to create data clusters according to similarity of data patterns over time, which in this case was used as a variable indicating students' engagement. Pazzaglia et al. identified six types of engagement patterns: (a) an initial 1.5 hours per week, decreasing over time (8%); (b) a steady 1.5 hours per week (39%); (c) an initial two hours per week, and then a spike in the final week (4%); (d) a steady 2.5 hours per week (38%); (e) consistent engagement of four hours per week or more (8%); and (f) high but variable engagement averaging approximately six hours per week (4%). The study also revealed that students who engaged for two hours or more per week had relatively high levels of course performance. It should be noted, however, that Pazzagalia et al. excluded credit recovery (CR) cases from their study sample. As such, students who took online courses to recover credits they previously failed to earn were not represented.

The above review of previous micro-level examinations of online learning success emphasizes that a more comprehensive model is required, by going beyond the aggregate variable and including a more nuanced understanding of engagement in online learning. It may be useful to begin by recognizing that the construct of learning engagement in online courses consists of two distinct dimensions—engagement levels and engagement patterns—which in turn implies that any such model should encompass both. The dimension of engagement patterns is especially important in online learning contexts, which tend to be characterized by requirements for learner autonomy more than other learning settings. In other words, unlike conventional brick-and-mortar classrooms with fixed schedules for interaction with both the course materials and the instructor, online learning allows such interaction to be self-directed by students. Accordingly, it seems unwise to group all students with total login durations of 80 hours, irrespective of whether this resulted from a consistent effort of four hours per week throughout the semester or from intensive time investment during just a few key weeks.

The present study also took the position that students' motivation to take online courses should not be overlooked, especially in the case of the CR group. As well as struggling to master the content itself, CR students may face new challenges associated with its unfamiliar formats and the new requirement that they must learn how to self-direct their learning. However, no previous study has focused on this specific learner group, and, therefore, the present study sought to fill this research gap.

In sum, to provide a complete picture of successful online learning in Michigan during the year in question, this study aimed to take up a key perspective at the micro-level by examining students' learning behavior and its association with their course outcomes. It is guided by the following two research questions:

1. What online learning profiles emerge from LMS data on student engagement in online courses?
2. How were student-information and learning-behavior factors, that include learning profiles generated by research question one, associated with learning outcomes in online courses?

METHODS

Study Site

This study examined MVS's LMS data from the 2015-16 school year. MVS is an accredited state-wide virtual school and comprises a program of a la carte online courses that students can use to supplement the learning experiences provided by their brick-and-mortar schools or home schooling. MVS is not a full-time program and does not award high school diplomas.

During the year in question, MVS offered 225 courses, mostly in core academic and foreign-language subjects, and had 24,448 course registrations from 14,555 students. Some of the courses were developed by MVS, and others used licensed content from nationally-recognized providers. All the MVS-designed courses were reviewed by a third-party quality assurance program and certified as compliant with its quality standards. Across courses, students used digital texts and various interactive learning materials and methods, including streaming audio and video, computer animations, email, chatrooms, digital portfolios, individual and team projects, and discussion forums. Learning was self-paced, and communications between and among teachers and students were asynchronous (Michigan Virtual University, 2016).

All courses followed the state and/or national curriculum standards and were taught by state-certified teachers with endorsements for the relevant content area and grade level. Though each course was fully designed, instructors were allowed to supplement and personalize learning materials as circumstances demanded. Their primary roles, however, were to support students' learning through communication with them, their parents/guardians, and their mentors at their own respective schools; to provide progress-monitoring and informative feedback; and to facilitate specific student tasks and activities, especially class discussions.

Study Sample

As mentioned previously, MVS student populations are higher achieving in both their face-to-face and online courses than students who are enrolled in other online learning solutions (Freidhoff, 2017). However, even within the population of high achieving students, there is a subset who still struggle with their online courses, for example, students who are taking courses for credit recovery. In order for the study to explore factors while encompassing unique challenges of that subset of learners, the study sample was drawn from the highest enrollment courses by CR students, securing as many of those cases as possible.

The study sample was comprised of 1,049 enrollments from 788 students in 11 course categories, including civics (one course), U.S. history and geography (two courses), algebra (four courses), geometry (two courses), and English language and literature (two courses). Of the entire LMS data in the 2015-16 academic year, approximately 3% of total enrollments fell under the CR enrollment reason category, whereas just over 7% of the study sample consisted of CR students. The total enrollment cases in the study sample were split into groups based on the course-classification system utilized by School Courses for the Exchange of Data (SCED). According to its parameters, 47.4% of such cases were in social sciences and history, and 43.9% in mathematics. Females made up 56.7% of total enrollments.

Analytical Approach

Measurements. The main student learning outcome was measured by the percentage of points earned, that is, an aggregation of the students' performances on various assignments and multiple exams divided by the total possible points in the courses. As the indicator of course-engagement level, the research team used the total number of times during the semester that the course materials were accessed through the LMS and labeled it *Sessions*. The total hours spent on the LMS per student per semester was labeled *Hours*. When it comes to proxies for engagement pattern, results from time-series clustering analyses were used, as described in the following section.

Time-series Clustering. This method was selected based on our insight that a student's efforts within a course needed to be understood not merely via measurement of a single discrete type of behavior, but via a more comprehensive record of patterns over time (Pazzaglia, et al., 2016). A time-series analytic approach enabled the identification of such patterns by capturing intra-individual changes in the learning process. There were two representative data sources in the virtual school's LMS: the gradebook and timestamped log data. In the gradebook, attempted scores were recorded when students started activities that were assigned course points, such as assignments, quizzes, and tests; earned scores were recorded based on auto- and/or instructor-graded qualities of those activities. The week-by-week attempted scores were chosen with an assumption that the engagement pattern captured by attempted scores was a better proxy for resultant behaviors derived from an individual's motivation. The second type of time-series data, week-by-week time spent in the LMS, were calculated using the login and logout timestamps for each session; time-series clustering was then applied to place students in subgroups based on their patterns of time investment over each 20-week semester.

Both types of time-series data underwent partitioning clustering computations using "tscluster" packages (Sardá-Espinosa, 2017). To select the optimal numbers of clusters, various cluster-validity indices (CVIs), including the Silhouette index, Dunn index, COP index, Davies-Bouldin index (Arbelaitz et al., 2013), and Score Function (Saitta, Raphael, & Smith, 2007), were calculated and evaluated. Clustering results were summarized in centroid plots and descriptive statistics provided for the characteristics of their members in terms of gender, CR reason, subject areas studied, course-engagement levels, and the average final grades. The categorical variables that were generated by this time-series clustering analysis were included in the regression model as indicators of engagement patterns.

Regression Analysis.

To link course outcomes to various explanatory variables including student background information, aggregate engagement, and engagement patterns, a series of regression models was tested using Stata version 14. In such models, categorical variables have distinct reference groups. As reference groups for gender and enrollment reason variables, *females* and *reasons other than CR* were used. The variable of subject area was modeled based on the reference group *Social*, such that *ELL* and *Math* denoted coefficients for those subjects in comparison with social science and history, respectively. When the categorical variable generated by time-series clustering analysis was modeled, we used dummy coding that required us to choose the reference group. Clustering results with the profiles in which the trends "final spike" or "procrastination" stood out in their centroid plots were the reference group. Thus, the model test results can be expected to reveal significant success factors for students who actively engaged with a given course during its final several weeks.

The researchers hypothesized that the association between session counts and course outcomes would vary across subject areas. With that in mind, interaction effects were tested. In the model for interaction effects, simple slopes for all levels of a categorical variable were presented, and follow-up statistical tests of difference were denoted by "minus." For instance, "Math minus Social" denoted a difference test between two coefficients of the total sessions between the mathematics-course group and social science/history-course group. The current study also hypothesized that the relationship between login duration and course outcomes might not be linear. For instance, very prolonged times in the LMS could signify students' struggles with or distractions from course content. For this reason, the researchers tested quadratic terms for the variable *Hour*s. The Appendix lists variables that were modeled and the full model was tested with the equation shown below:

$$Final\ Grades = \alpha + \beta_1 Male + \beta_2 Credit\ recovery + \beta_3 Math + \beta_4 ELL + \beta_5 Consistent + \beta_{6.1} Steady + \beta_{6.2} High\ Amount + \beta_7 Sessions * Math + \beta_8 Sessions * ELL + \beta_9 Sessions * Social + \beta_{10} Hour + \beta_{11} Hour^2$$

FINDINGS

As noted above, two types of time-series data were used for clustering the individuals in the study sample into subgroups based on their time-series patterns. The resultant centroid plots in Figure 1 summarize the respective behavioral profiles for each of these data-driven clusters. The X axis indicate the time variable in weeks, and the Y axis shows the percentage of students' attempted scores or the login duration in minutes.

Learner Profile of Engagement Pattern for the Fall Semester

Evaluation of the CVIs of the fall semester data indicated the existence of two motivational profiles vis-a-vis course completion. The centroid plot of the first cluster from Attempted-Score (top left panel in Figure 1) shows a gradual increase in the cumulative scores students attempted to earn each week as a percentage of possible course points: from 0% in the first week to 100% at the final week. The second cluster's centroid plot, meanwhile, can be characterized as a long stretch of inactivity throughout the first three-quarters of the course, followed by a final spike reaching to about 40%. On the basis of those observations, we labeled the first cluster "consistent attempters" (n=396) and the second one as "procrastinators" (n=124).

For the same semester, time-series clustering using week-by-week cumulative minutes recorded in the LMS indicated the existence of two clusters with regard to time-investment patterns, the first being "final spikers" (n=276) and the second, "steady increasers" (n=243). Notably, though both groups were roughly the same size, the "final spikers" graph peaks at 1,250 minutes, i.e., less than one-third of the time invested by the "steady increasers."

Learner Profile of Engagement Pattern for the Spring Semester

Clustering the weekly gradebook data from the spring semester (top right panel in Figure 1) also revealed two types of engagement profiles. Around 77% of the members of the spring semester sample were "consistent attempters" who strove to complete their tasks week by week. Unlike the fall semester's cluster with a similar profile, however, a semi-parabolic shape stands out, indicating that these learners' efforts were off to a slow start during the first half of the spring semester. According to the CVIs, on the other hand, there were three distinct groups by type of engagement patterns. The first was labeled "high amount," due to its maximum value of 5,000 minutes, far greater than the other two clusters' values. In this group's centroid plot, a consistent and rapid increase from week 10 stands out. The second, comprising approximately one-third of the spring sample, were members of the "final spikers" group, whose time-investment in the course seems to have begun at week 15. Finally, half the spring sample exhibited relatively consistent, but gradually rising time investment throughout the spring semester and were thus labeled "steady increasers." Given that the spring semester data generated a distinct group of learners who steadily spent considerable time in the LMS, it is unsurprising that the spring "steady increasers" group has a less steep slope over the weeks than its fall counterpart does.

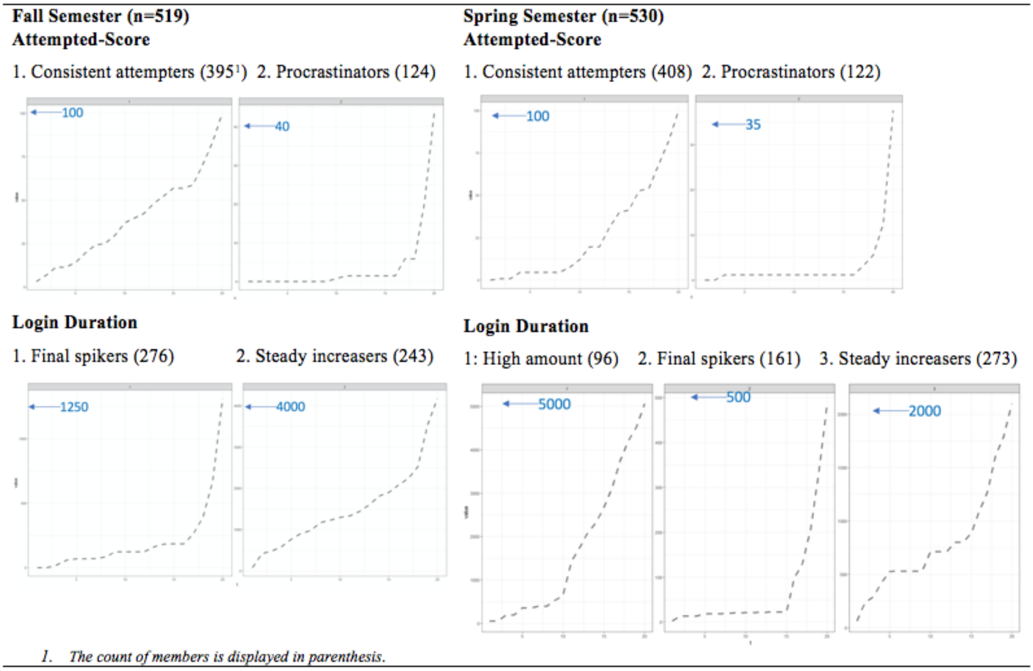

Figure 1. Centroid Plots

Characteristics of Engagement Pattern Profile

The characteristics of the data-driven subgroups described above are summarized in Table 1, which includes (in percentage form) the numbers of enrollments by male students, CR reasons, and types of subject areas as classified by SCED. The percentages shown in the table can be compared across clusters as well as against the corresponding percentages in each semester's sample as a whole. Table 1 also presents summary statistics for final grades, login counts, and total hours in the LMS for individual clusters as well as for each semester's sample.

The "procrastinators" cluster's percentages of students who were male, had CR enrollment reasons, and were studying math were markedly greater than corresponding percentages in the fall semester sample as a whole. The "consistent attempters," in contrast, had higher averages and lower standard deviations in aggregated course-engagement indicators (total sessions and total hours) and course outcomes (final grades) than both the "procrastinators" and the fall semester sample as a whole. In terms of clustering results from the time-investment perspective, “final spikers” were more likely to be male, to have CR enrollment reasons, to be taking ELL courses, to have low levels of course engagement, and to have poor course outcomes.

Observation of clustering results for the spring semester reaffirmed that CR and male students were more likely than others to be “procrastinators” and “final spikers.” ELL courses were also more closely linked to clusters with those two less-desirable profiles than ELL courses should have been in the spring semester sample as a whole. It should also be noted that mathematics enrollments made up 62.5% of the “high amount” cluster as well as 49.8% of all spring semester enrollments. Accordingly, it is more likely to find students who spent a considerable time in the LMS who were enrolled in mathematics courses.

Lastly, final grades were regressed on various explanatory variables including student background information, aggregate engagement, and engagement patterns. The results are summarized in Table 2 and are discussed in the next section.

Table 1
Descriptive Summaries of Clusters

	Fall Sample	Attempted-Score		Login Duration		Spring Sample	Attempted-Score		Login Duration		
		Consistent	Procrastinated	Steady Increase	Final Spike		Consistent	Procrastinated	Steady Increase	High Amount	Final Spike
Obs.	519	395	124	243	276	530	408	122	273	96	161
Male %	43.35%	41.77%	48.39%	38.68%	47.46%	42.83%	40.44%	50.82%	42.29%	38.54%	45.96
CR%	9.06%	6.84%	16.13%	4.53%	13.04%	5.66%	4.66%	9.02%	4.4%	5.21%	8.07%
ELL%	8.67%	8.61%	8.87%	6.58%	10.51%	10.38%	9.31%	13.93%	9.52%	6.25%	14.29%
Math%	43.93%	40%	56.45%	43.62%	44.2%	49.81%	50.25%	48.36%	48.35%	62.5%	44.72%
Social%	47.4%	51.39%	34.68%	49.79%	45.29%	39.81%	40.44%	37.7%	42.12%	31.25%	40.99%
Total Sessions											
Avg.	87.77	98.79	52.69	107.74	70.19	75.9	87.49	37.16	80.14	112.11	47.12
Std. Dev.	41.88	35.35	41.87	38.28	36.79	42.55	38.97	29.06	32.45	45.45	36.32
Min.	0	23	0	38	0	0	14	0	22	41	0
Max.	257	257	251	257	185	298	298	138	208	298	144
Total Hours											
Avg.	40.33	45.19	24.85	64.09	19.42	36.64	43.33	14.24	35.81	86.95	8.04
Std. Dev.	30	29	27.89	26.07	12.61	30.72	30.39	19.08	10.3	29.62	8.76
Min.	0	0.65	0	31.14	0	0	0.44	0	13.87	50.44	0
Max.	172.33	172.33	168	172.33	64.05	233.89	233.89	132.69	67.96	233.89	54.64
Final Grades											
Avg.	72.79	84.48	35.54	85.2	61.86	71.58	85.19	26.07	81.97	87.35	44.57
Std. Dev.	27.94	11.63	31.9	14.28	32.18	30.18	10.83	29.58	16.28	10.02	37.86
Min.	0	41.77	0	10.95	0	0	43.99	0	6.69	57.46	0
Max.	99.55	99.95	99	99.36	99	99.73	99.73	93.12	99.45	99.73	99.5

Table 2
Regression Models

Model Semester (Adj. R2)	Negative	Positive	Not Significant
Model 1. Gender			
Fall (0.68%)	Male -5.25(2.47)*[1]		
Spring (0.87%)	Male -6.26(2.64)*		
Model 2. Credit Recovery			
Fall (3.15%)	CR -17.7(4.21)***		
Spring (0.98%)	CR -14.09(5.65)*		
Model 3. Subject Area			
Fall (1.79%)	Math -8.62(2.55)***		ELL -3.81(4.49)
Spring (1.49%)	ELL -13.03(4.54)** Math -6.13(2.77)*		
Model 4. Total Sessions			
Fall (26.93%)		Sessions 0.35(0.03)***	
Spring (31.53%)		Sessions 0.40(0.03)***	
Model 5. Total Hours			
Fall (20.64%)		Hours 0.42(0.04)***	
Spring (22.09%)		Hours 0.46(0.04)***	
Model 6. Attempted-Score-Cluster			
Fall (55.81%)		Consistent 48.95(1.91)***	
Spring (68.07%)		Consistent 59.12(1.76)***	
Model 7. Login-Duration-Cluster			
Fall (17.24%)		Steafy 23.33(2.24)***	
Spring (35.20%)		High Amount 42.78(3.13)*** Steady 37.40(2.41)***	
Model 8. Interaction Between Total Sessions and Credit Recovery			
Fall (28.03%)		CR's Sessions 0.34(0.14)*** Non-CR's Sessions 0.34(0.03)***	CR -11.72(7.79) Non-CR minus CR -0.03(0.1)
Spring (31.64%)		CR's Sessions 0.48(0.09)*** Non-CR's Sessions 0.39(0.03)***	CR -12.59(9.95) Non-CR minus CR -0.09(0.15)

Table 2, *Continued*

Model Semester (Adj. R2)	Negative	Positive	Not Significant
Model 9. Interaction Between Toatl Sessions and Subject Area			
Fall (29.86%)		ELL'sSessions 0.48(0.09)*** Math's Sessions 0.29(0.03)*** Social's Sessions 0.4(0.04)*** ELL minus Math 0.19(0.1)* Social minus Math 0.11(0.05)*	ELL -7.61(8.9) Math 0.91(5.04) Social minus ELL -0.08(0.1)
Spring (33.94%)	ELL -30.9(7.31)*** Math -11.6(4.73)*	EILL Sessions 0.57(0.07)*** Math's Sessions 0.4(0.03)*** Social's Sessions 0.33(0.04)*** ELL minus Math 0.17(0.08)* Social minus ELL 0.-0.24(0.08)**	Social minus Math -0.07(0.05)
Model 10. Concave Relationship Between Total Sessions an Subject Area			
Fall (30.63%)	Quadratic/Hours -0.01(0.001)***	Linear/Hours 1.14(0.09)***	
Spring (34.13%)	Quadratic/Hours -0.006(0.001)***	Linear/Hours 1.15(0.08)***	
Full Modeal			
Fall (66.28%)	CR -5.69(2.57)* Steady -5.97(2.47)* Quadratic/Hours -0.004(0.001)**	Consistent 36.88(2)*** ELL's Sessions 0.18(0.06)** Social's Sessions 0.12(0.03)*** Linear/Hours 0.7(0.09)*** ELL minus Math 0.14(0.07)* Social minus Math 0.08(0.04)*	Male -1.07(1.47) ELL -0.87(6.25) Math 3.94(3.5) Math’s Sessions 0.04(0.03) Social minus ELL -0.05(0.07)
Spring (76.02%)	ELL -13.86(4.5)** Math -9.1(2.87)** High Amount -22.3(4.64)*** Steady -5.5(2.61)* Quadratic/Hours -0.003 (0.0005)***	Consistent 46.85(1.99)*** ELL’s Sessions 0.16(0.05)** Math’s sessions 0.11(0.03)*** Social’s Sessions 0.07(0.03)** Linear/Hours 0.68(0.09)**	Male -1.54(1.33) CR -2.08(2.87) ELL minus Math 0.05(0.05) Social minus Math -0.03(0.04) Social minus ELL -0.09(0.05)

1. Asterisk denotes the probability < 0.001, <0.01, and <0.

Simple Regression Models

Across both semesters, enrollments from male students, for CR purposes, and in mathematics courses were negatively associated with course outcomes. On the other hand, course outcomes were positively related to variables pertaining to course engagement, including total logins *(Sessions),* level of time-investment *(Hours)*, and being a “consistent attempter” *(Consistent)* or a “steady increaser” *(Steady)*. The course of mathematics was a negative factor for both semesters, but a distinction between the semesters could be made, insofar as there was a stronger negative association between ELL and course outcomes in the spring semester. It should also be noted that one more cluster, *High Amount*, was derived from the spring semester’s time-investment data than from the fall semester’s, and the membership of that group were more likely to perform in the course successfully than were the “final spikers.”

Interaction between Login Frequency and Subject Areas

To test the hypothesis that the association between session counts and course outcomes would vary across enrollment reasons and subject areas, interaction effects were tested. Simple slopes of final grades on total number of logins were significant for both the CR and non-CR groups and for all three subject areas. However, significant differences in session counts’ effects were found in comparisons of math vs. ELL and math vs. social science in the fall data, and ELL vs. math and ELL vs. social science in the spring data. Taking both semesters’ results together, there was a consistent pattern: the total number of course logins was a success factor for all three subject areas, but overall, its associations with final grades tended to be weaker in mathematics courses and stronger in ELL courses.

Concave Relationship between Login Duration and Final Grades. On the basis of the hypothesis that the relationship between login duration and course outcomes might not be linear, the researchers tested quadratic terms for the variable of *Hours* and found a curvature in the relationship, according to the statistically significant coefficients of the linear as well as quadratic terms. The turning point to the downward trend (i.e., the vertex of the parabola) occurred at 92 hours (4.6 hours per week, on average), and 6% of the fall semester sample met this criterion, i.e., having stayed logged into the LMS for more than 92 hours in total. The spring semester’s global extremum of the relationship, meanwhile, was found at 103 hours (5.15 hours per week, on average), and enrollments on the downward relationship made up 4% of that semester’s sample. In other words, for approximately one in 20 of the students in either semester, longer durations spent in the LMS could not be expected to result in better achievement.

Full Regression Model. Finally, the full model tested all hypothesized relationships and accounted for 68% of variance in the final grades of the fall semester sample. Course achievement's positive relationship with "consistent attempter" behavior and its negative relationship with CR status both remained statistically significant. However, when covariates were introduced into the model, the previously observed negative relations between course outcomes, on the one hand, and, on the other, taking mathematics or ELL courses (as compared to social science courses) and being male were found to not be statistically significant.

The total number of logins was a significant predictor of final grades in the simple model (Total Sessions in Model 4). When the variances attributable to login times were partitioned into three groups by subject area, this relationship became non-significant in the case of mathematics courses. However, it remained significant and strong in the case of ELL courses and significant but weak in the case of mathematics courses.

With regard to login duration, after controlling for the effect of other factors, the full model still revealed a concave relationship between total hours and final grades. Interestingly, being a "steady increaser" was significantly and negatively associated with final grades. That is, a consistent week-by-week time investment was a positive factor in general, but all else being held constant, having it as one's course-engagement profile was a negative factor for course success – even as compared to being a "procrastinator." Accordingly, if a sufficient range of other factors is taken into consideration, a particular learning profile based on time-investment patterns – however desirable in theory – will not necessarily have a clear relationship to students' success in online courses.

In the spring semester data, the only two relationships that remained statistically significant in the final model were "consistent attempter" status (positive association with achievement) and mathematics or ELL enrollment (negative association with achievement). Being male or having CR as one's enrollment reason were not significant factors in course success after other covariates were taken into consideration. With regard to total numbers of logins, significant simple slopes for all three subject areas and none of the significant difference tests indicate that login frequency was a success factor in all course subjects and of equivalent importance for all of them. The variable of login duration was also a consistent success factor, within certain ranges. The spring semester data reaffirmed the inconsistency of predictor variables specified from time-series clustering results using week-by-week login duration.

Lastly, partial eta squared was calculated for each variable's effect size estimation, and all results are summarized in Table 3. The results highlighted one of the most powerful success factors: having the "consistent attempters" profile of those who strive to complete course work week by week. It explained the total variance for the final course grade for 40% of fall semester and 52% of spring semester.

Table 3
Effect Size Estimation

Source	Partial Eta Squared	
	Fall	Spring
Male	0.001	0.003
Credit Recovery	0.01	0.001
Attempted-Score-Cluster	0.402	0.517
Login-Duration-Cluster	0.011	0.061
Subject Area	0.003	0.027
Interaction of Subject Area by Total Sessions	0.044	0.053
Total Hours	0.103	0.1
Quadratic Term of Total Hours	0.068	0.066

DISCUSSION

The current study first explored Michigan's policy and legislative system of K-12 online learning and trends of enrollment and performance and then examined micro-level factors to help gauge whether or not a student is likely to complete their online course successfully. From the full model, the study found that consistently and persistently attempting to complete assignments throughout the semester was a crucial success factor. The total frequency of LMS logins was also another success factor for English or social science courses, whereas it may not be as reliable to predict the success in mathematics courses, reiterating Hung et al.'s findings (2012). In mathematics courses, frequent logins do not always signify students' success but, rather, may imply that students are struggling with content mastery (thus revisiting the content frequently) and not engaging in the prolonged sessions with the course content that is required for deep learning.

To the existing evidence of a positive association between the total time in course and grades (Liu & Cavanaugh, 2011), this study added that the total time is a positive factor but has a threshold to continue to impact positively through a significant concave relationship between login duration and final grades. For those one in 20 students who experienced poor outcomes with extended log in times, there are a number of possible reasons. First and most simply, there is a possibility that these students were not actively engaged in the course but rather still logged into the course, as the LMS in the study was set to log students out automatically only after four hours of inactivity. Second, for the students who spend extended time in the LMS, their activity does not lead to successful course outcomes, and they may be spending more time in the LMS because they are struggling to progress through the course content. It may be inefficiency or gaps in understanding and certainly suggests a space where on-site mentors may be able to provide support to the student to get them back on track. Therefore, if students appear to stay in the LMS too long, for instance longer than four or five hours per week, the educators who are supporting students may need to question students' alertness, concentration, focus, efficiency of learning behaviors in the LMS, and content mastery.

Another intriguing result related to login duration is the state of being constantly logged into the LMS week by week, which was not a success factor when other behavioral indicators and conditions were taken into consideration. Pazzaglia and colleagues' study (2016) may provide a plausible explanation for this counterintuitive result on steady time investment. The study demonstrated four types of successful learning profiles based on week-by-week login duration over the semester, including (a) initial 2 hours with final spike, (b) steady 2.5 hours, (c) steady 4+ hours, and (d) variable 6+ hours. Those groups had similar course outcomes on average, and being members of any one of them was positively related to course outcomes despite their unique engagement patterns. More importantly, the profile of steady 1.5 hours per week was not associated with the successful learner group. Taken all together, being steady in terms of time investment in the LMS is not a key; rather, effective time investment would seem to be critical, but this can take various forms.

Given that interpretation, we may need to refine the notion of time management. Time management has been emphasized consistently as a critical factor for success in online learning. For example, in the Online Self-regulated Learning Questionnaire (OSLQ), time management based on allocating and scheduling study time was a valid and reliable indicator of self-regulated online learning (Barnard, Lan, To, Paton, & Lai, 2009). However, it is notable that time management does not simply translate into setting aside blocks of time to study; for instance, there is a question that states, "Are you willing and able to spend 2 hours on your virtual course?" In addition to that, there is a need to understand more nuanced notions of time management, such as how to make good use of study time and how to identify and eliminate time wasters and bad study habits in the LMS specifically and in the online learning context in general.

Unlike the pattern of steady time investment, being profiled as "steady increase in attempted scores" was found to be significant in both simple and full models. That is, consistently and persistently attempting to complete course assignments was predictive of success when everything else was held constant. Note that the study used the attempted score rather than the score that a student actually earned week by week. Although the attempted score would be highly correlated with the earned-score, we believed that study results using the former was more likely to provide us with a space to discuss self-regulated learning (SRL). Although from this study, one cannot determine how exactly those students are and are not self-regulated. It is reasonable to infer that various SRL skills, such as goal setting, effort regulation, help-seeking, and metacognitive strategies would come into the behavior as students are steadily attempting to accomplish their learning goal (Zimmerman & Schunk, 2001). Further research should consider examining characteristics of those successful students' SRL based on not only the level on the scale of SRL measures but also the profile across various SRL dimensions (Barnard-Brak, Lan, & Paton, 2010), which would enable us to understand what components of SRL skill sets are needed and to what extent the components lead to the behavioral pattern of steady increase in task completion week by week.

The full model also indicated that both level and pattern of course engagement could make the effects of non-malleable factors, such as gender, disappear or at least lessen. That is, results from the simple model were consistent with evidence for gender difference in online learning (Lowes, Lin, & Kinghorn, 2016), but gender difference was no longer significant in the full model once malleable factors, that is, learning behaviors, were taken into consideration. Hence, course design features, instructional practice, and support structures that bolster a student's active engagement in the LMS, and probably with other learning materials, may narrow the gender gap in online learning.

When it comes to the CR enrollment reason, its negative association with course outcomes remained significant for the fall semester sample but disappeared for the spring sample of the study. This finding may be explainable in two ways. First, this result implies that the negative effect of CR status was offset to some degree by incorporating learning behavior related variables, reiterating the significance of learning behaviors in successful online learning. Second, the smaller size of CR enrollments in the spring (6%) compared to the fall sample (9%) could give a result which was not sufficiently powered to detect statistical differences. Consistent with Kwon's findings (2017), a negative relationship between CR enrollments and successful online learning exists, and the study therefore suggests that the level and pattern of engagement in the LMS does not sufficiently mitigate it. Accordingly, this population may have unique needs for them to succeed in online learning (Oliver & Kellogg, 2015). According to a rigorous evaluation of multiple sites (Levin, Johnson, Malave, & Santaniello, 2017), online

CR programs could produce some positive outcomes (e.g., graduation rate) but not others (e.g., college enrollment after graduation and state-wide high-stake tests); additionally, some impacts endured while others faded (e.g., dropout deterrent). This variation in outcomes is disappointing given that online CR programs have been assumed to be an alternate approach to a traditional one whereby students may encounter the same content, the same vehicle to learn them, and in some cases even the same teacher as the situation within which they previously failed. To improve program quality and support structures, voices from the CR population who succeeded in online learning would be helpful.

LIMITATIONS

Although the study succeeded in its aim, there are some unavoidable limitations. First, omitted variable bias may occur. Omitted variables may include student self-regulated learning characteristics, access to computer and internet connection, the quality of support from schools, and families, and course- and instructor-level factors. These may positively impact course outcomes and one or more explanatory variables in the model (e.g., learning engagement indicators), and therefore our model may suffer from upward bias by letting the explanatory variable actually account for the effects of those omitted variables. We were unable to include those variables in the model because their effects on learning outcomes were unexplored by previous research and remained unknown, calling attention to several topics in need of further investigation.

Second, despite its usefulness, there was an issue with using timestamp data for capturing student learning engagement. This is because there was no timestamp for when a student left a session or for how long a student was inactive in the LMS, so the log-in duration may be an overestimate and/or does not map to "real-world" time working on the course. Yet, the relative differences between students would be the same, as the data would be consistently skewed – therefore, statistical analysis, particularly data use for the engagement pattern, can be trusted as there is a common foundation.

Additionally, the variable of enrollment reason relied on only what was reported when students enrolled in MVS because the data missing the enrollment reason variable would have produced inaccurate reports. Pertinent results represented comparisons between students who specified CR as their enrollment reason and those who chose another enrollment reason category, such as schedule conflict, or declined to report it.

CONCLUSION

The findings from this study have been both supportive and contradictory of previous research. With this in mind, the implication moving forward is to continue to conduct research to inform the field which clarifies our understanding of successful online learning. Since one of the study's foci was on the various learner groups available in the data, its sample was drawn from the highest enrollment courses by CR students, securing as many of those cases as possible. As such, presented results provide empirical evidence to substantiate successful learning in mostly core subject areas and point to several promising areas for future research. To reach a fuller understanding of successful learning in various online courses, researchers need to look at other elective, Advanced Placement, and foreign language courses that expand the options available to students who have limited access to those courses from their brick-and mortar schools.

The study began by clarifying Michigan's contexts of K-12 online education focused on upper-level systems, including policy and legislative infrastructure and public perceptions (Bronfenbrenner, 1977) and found that the field, over the last two decades, has seen an exponential increase in the number of schools under the auspices of those systems. The authors also examined a more-fine grained aspect, students' actual learning behaviors and outcomes in their online courses. While it may seem as if there is a divide between state policy and legislation and students' learning behaviors and outcomes, the analysis was done in hopes of generating findings and subsequent implications which in turn can serve to inform the specificity component of policy implementation (Porter, 1994; Porter et al., 1988) for the next decade.

It will be important for all educational stakeholders to keep a finger on the pulse of trends in their state and communities in order to understand the needs of their constituents and to inform them of all the learning options, as well as the supports for those options in online learning environments. Information on how to succeed in online learning should include one of the key findings in the study—the importance of steady attempts to complete learning tasks, ideally with students' own self-regulated learning scaffolded by course pacing guides. When it comes to quality assurance of programs, some conclusions may be drawn that course design features, instructional practice, and student support structures meet the learner needs from the perspective of good pacing and a good use of study time.

The results also highlight the importance of quality assurance within legislation and policy. In particular at this level is the provision of guidance for programs, especially those that are offering CR options for students. State legislation and policy relative to quality assurance for education programs offering online learning would be helpful if not already in place.

AUTHOR NOTE

The three authors have affiliations with the organization that was the study site as employment, and thus, have financial interest in the subject matter or materials discussed in this manuscript. However, the authors are specifically affiliated with a research institute housed within in the organization that is committed to the principle of free, open, and objective inquiry in the conduct of research. Also, none of the authors were involved in the administration of the learning management system or collecting data that was used by the study.

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APPENDIX

Variable Definition (Variable Name)
• Male (Male)
• Credit recovery in comparison with all other enrollment reason categories (CR)
• Mathematics in comparison with social studies (Math)
• English language and literature in comparison with social studies (ELL)
• Total sessions (Sessions)
• Total Hours (Hours)
• Time series clustering results of attempted scores—Consistent attempters in comparison with procrastinator (Consistent)
• Time series clustering results of login-duration—Steady increase in comparison with final spike pattern (Steady)
• Time series clustering results of login-duration—High amount of time investment in comparison with final spike pattern (High Amount)
• CR by Sessions Interaction
• Subject area by Sessions Interaction
• Quadratic term of Hours