Examining CREDIT RECOVERY EXPERIENCE at a State Virtual School

March 2017

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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 University*® (*MVU*®) to establish a center for online learning research and innovation, and through this center, directed *MVU* to work on a variety of projects. The center, known formally as *Michigan Virtual Learning Research Institute*™ (*MVLRI*™), is a natural extension of the work of *MVU*. Established in 1998, *MVU*'s mission is to advance K-12 education through digital learning, research, innovation, policy 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.

MVU 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 *MVU* staff to provide research, evaluation, and development expertise and support.

About the Credit Recovery Series

Michigan Virtual Learning Research Institute (MVLRI™) has launched a series of quantitative research 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 – two using *MVS* data and one using data from schools in other states – will place more fine-grained variables at the analytic center by examining students' engagement patterns in their courses. Some of the subject areas most frequently taken by CR students will be targeted and weekly time-stamped data, for example, time spent in the course across weeks, will be analyzed based on hierarchical clustering methods of time-series data to depict data-driven learner groups and the plausible interpretation of their behavioral patterns. Finally, data from different state virtual schools will be examined focused on any commonalities and differences across virtual schools, just as will be done with the reports based.

Suggested Citation: Kwon, J. B. (2017). *Examining credit recovery experience at a state virtual school.* Lansing, MI: Michigan Virtual University. Retrieved from http://media.mivu.org/institute/pdf/creditrec.pdf

Executive Summary

The first report begins discussion on the topic by testifying to the concept that students who have different reasons for taking online courses perform differently. Specifically, the underperformance of credit recovery students was hypothesized; the contextual information was also explored, including enrollment patterns, demographic factors, and the learning environment which focused on instructors who taught the courses. From descriptive analyses and cross-classified multilevel modeling using data from 24,437 course enrollment records from 14,551 students, key findings showed that more students enrolled in *MVS* mathematics courses and summer courses for CR than for any other reason. Analysis also revealed that those students were more likely to underperform in comparison with those indicating any other enrollment reason while controlling for variance due to student gender, instructor types, and the data structure.

The author discusses implications of findings for practice, policy, and research. It appears that if *MVS* wants to examine the content delivery structure and/or student support system focused on CR, it is advisable to make Algebra courses a priority and that launching special summer credit recovery programs also deserves earnest consideration. The result also highlights that it is important to establish robust support structures in online learning – more so in the context of remediation than acceleration. The support structure should build upon mutual goals for student success, shared accountability, and shared resources among course providers, schools, and districts. With regard to research, further exploration needs to focus on the association of student learning outcomes with instructor characteristics measured by other factors than one that was used in the present study (i.e., instructor position types), for example the quantity and quality of interactions between instructors and students. The question has also been raised about variance in learning outcomes that is associated with variation in mentor supports at the school/district level so as to gain insight into elements of instruction and supports that ensure student success in online courses.

Introduction

Since 2010, after adopting a uniform method for calculating graduation rates, the U.S. Department of Education reports that the nation's high school graduation rate increased to 82.3% in 2013-14 (U.S. Department of Education, 2015). Yet, the breakdown of data by subgroups shows that gaps still exist between the national average graduation rate and the graduation rate of students whose English proficiency is limited (19.7% difference), students with disabilities (19.2% difference), students who are a racial or ethnic minority (12.1% difference for American Indian/Alaska Native, 9.8% difference for Black, and 6% difference for Hispanic), and students who are economically disadvantaged (7.7% difference). As state and local efforts to make continued progress and close those gaps continue, various types of credit recovery programs have been offered, and the use of online courses for credit recovery (CR) has grown in order to help students stay on track for graduation (Picciano, Seaman, Shea, & Swan, 2012).

Educators acknowledge that online learning is an effective way to reach students who seek an alternative to traditional courses after their failure in one or more of them. Notable examples of such programs include Montana Digital Learning Academy's (MTDA's) CR courses, West Virginia

Virtual School's onTargetWV, Florida Virtual School's intensive summer CR courses, and Alabama ACCESS (Powell, Roberts, & Patrick, 2015). Furthermore, many state virtual schools allow their courses to be taken for CR. In light of this development, a critical question has arisen: How does online learning currently functions as an option for students trying to stay on track to graduation? Studying this issue could help gauge the strengths of such programs and identify possible areas for improvement when designing or implementing credit recovery programs in an online learning context.

Despite the paucity of studies, several recent quantitative research analyses using data from state virtual schools, state online CR courses, and experimentally designed CR programs have helped shed light on this topic. Research findings are summarized in Table 1.

Table 1. Summary of Findings from the Credit Recovery Quantitative Research

Author (Year)	Region	Key Findings
Hughes, Zhou, & Petscher (2015)	Florida	High school students in online courses are more likely to earn a grade of C or better in their credit recovery efforts than in face-to-face courses.
Heppen et al (2016)	Chicago	Students in Chicago showed more negative attitudes toward learning mathematics and were less likely to succeed when the summer algebra CR program was delivered in an online format rather than via a face-to-face model.
Stevens & Frazelle (2016)	Montana	In MTDA CR courses, the average passing rate in online CR courses is 57% with the lowest passing rates in courses on mathematics and English language arts.
Stallings et al (2016)	North Carolina	There was little difference in short-term success (e.g., end-of-course exam scores) between state virtual school CR students and other CR students in the state of North Carolina. On measures of longer-term success, state virtual school CR students showed a relatively negative result in terms of whether they graduated overall but a positive result in terms of whether they graduated on time – if they graduated.

The synthesis of the previous studies points to information gaps, including (a) research contrasting CR and non-CR enrollments within state virtual school data; (b) research exploring the contexts of CR enrollments and their performance in-depth; (c) research exploring the instructor-related dimension in CR enrollments' performance; and (d) research modeling the unique structure of data, cross-classified nested condition among enrollment, student, and instructor. In order to fill this information gap, the first report in a series consisting of quantitative research on credit recovery, undertaken by the *Michigan Virtual Learning Research Institute™* (*MVLRI*™) using *Michigan Virtual School*® (*MVS*®) 2015-16 data, addresses several research questions around enrollment and performance patterns pertaining to credit recovery.

Research Questions

Based on Ajzen's Theory of Planned Behavior (see Appendix for details on how the theory guided this study), the study aimed at depicting the characteristics and performance of credit recovery enrollments by answering such questions as:

- How are total and credit recovery enrollments distributed based on various demographic factors?
- How are total and credit recovery enrollments distributed across subject areas?
- How are total and credit recovery enrollments distributed based on instructor-related factors?
- What are the learning outcomes, as measured by course completion status and final grades?

Finally, the crux of the research question is:

- Do students who take courses for CR underperform compared to those who are enrolled for other reasons, while controlling for covariance due to other key factors or bias due to the data structure?

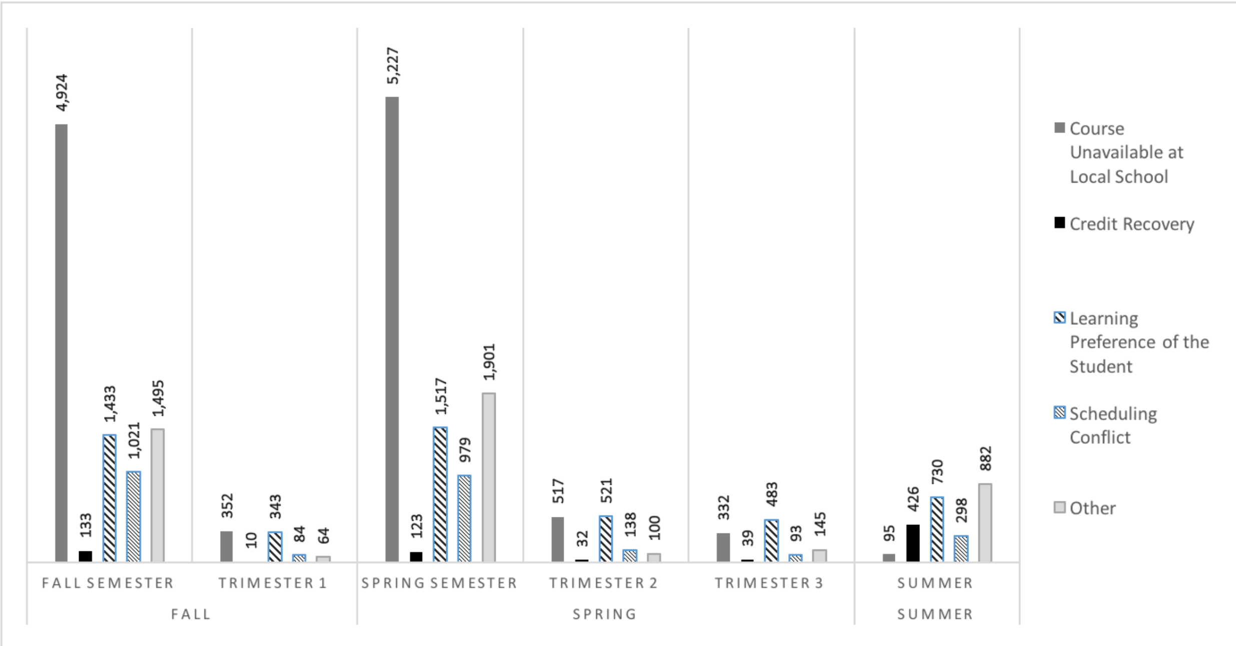
Methods

Data Source

This study used Learning Management System (LMS) data from the *MVS* 2015-16 academic year. *MVS* is a division of *MVU* that works in partnership with K-12 schools to supplement and expand online learning opportunities primarily for students in grades 9 through 12. *MVS* provides teacher-led online learning experiences for a broad range of core academic courses aligned with state standards, college-level equivalent courses, remedial, enrichment and world language courses. For the purposes of this study, data came from 24,437 *MVS* course enrollments and 14,551 students. Enrollments in spring, which includes the regular spring semester and two shortened periods called trimesters, were greater than those in fall.

There are four predefined reasons for enrollment that one may choose from when enrolling in an *MVS* course: course unavailable at local school, credit recovery, learning preference of the student, and scheduling conflict. An "Other" option was also available to collect additional qualitative data from the survey. Overall, 46.8% of total enrollments indicated "Course Unavailable" as their enrollment reason. The next most frequently chosen reason was "Learning Preference" (20.6%), followed by the "Other" category (18.8%). Only 3.1% of total enrollments fell under the CR enrollments category, and only a few (10.7%) took the *MVS* courses to resolve a schedule conflict. Figure 1 shows enrollment patterns by enrollment reasons within particular academic periods. During the fall period, 1.45 % (143 enrollment records) out of approximately 9,900 enrollments identified credit recovery as their enrollment reason, while credit recovery accounted for 1.6% of 12,147 enrollments in the spring. Many students enrolled in *MVS* summer courses for credit recovery, with 19.6% of 2,428 total enrollments being for this purpose.

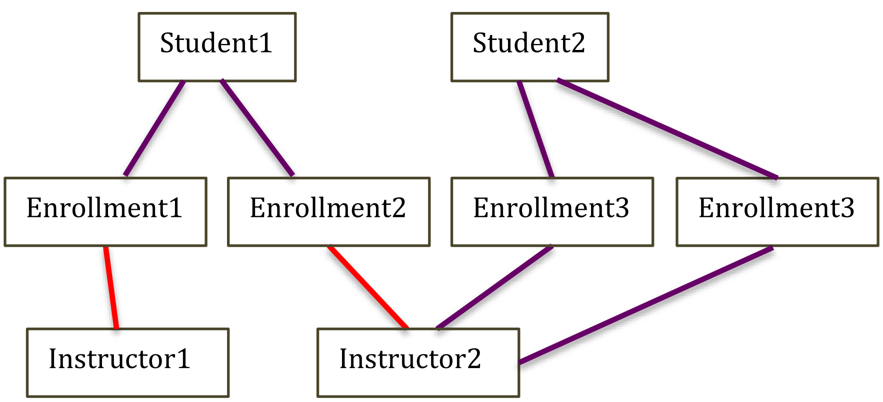
Figure 1. Enrollments Status by Enrollment Reasons



Analytic Strategy

First, key factors were explored descriptively, and then correlational analyses were performed in an attempt to investigate any associations among these factors. Cross-classified, multilevel modeling (University of Bristol, 2010) was used to address the unique data structure – course enrollment is nested in students and instructors, respectively, as depicted in Figure 2. The cross-classified, multilevel modeling allows for modeling data at enrollment-, student-, and instructor-level simultaneously.

Figure 2. Data Structure



We needed to determine how the analysis deals with enrollment records in which multiple instructors were involved due to such cases as co-teaching, vacation, maternity leave, or other extended absences. For instance, multiple instructors for one enrollment record accounted for 432 enrollment records during the fall season, and 44.4% of those enrollments were co-taught by a team of full-time instructors and iEducators, *MVS's* novice online teacher induction program. For details, see the report, iEducator *21st Century Digital Learning Core: Program Design and Reflection*.[1] Another 34.7% of those cases were for the CI-MSU program for Chinese classes developed by Confucius Institute at Michigan State University and offered by *MVS*. For the other cases, full-time and part-time instructors were involved concurrently.

To avoid data loss, an instructor's unique identifying (ID) number and their position type were re-coded for each enrollment record in which multiple instructors were involved. For example, a combination of instructor A and B was assigned a new instructor ID number and placed in a "multiple instructors" category for the instructor-type variable. The same new instructor ID and instructor-type category was assigned to enrollment records relating to the same combination of multiple instructors. A distribution of unique multiple-instructor cases and instructors' teaching assignments is presented in the results section.

In order to focus on credit-attempting enrollments, audit records (127) were removed from the analyses from which learning and teaching outcomes were assessed. The final data set contains: (a) 9,803 enrollment records for 8,369 unique students and 173 instructors during the fall period; (b) 12,134 enrollments from 9,799 students and 182 instructors during the spring period; and (c) 2,373 enrollments from 1,749 students and 82 instructors for the summer semester. Note that the number of instructors does not correspond to the headcount of instructors who actually taught classes during the academic term because of the unique coding scheme by which each of the enrollment-level instances with multiple instructors was assigned a respective instructor ID code.

Results

Demographics from the Full Exploration of Sample Data

To investigate the characteristics of distributions of the total as well as of CR enrollments by such contextual variables as demographic factors and subject areas, the full data set was explored prior to deleting audit cases. Table 2 summarizes the results. Regarding gender-related distribution, we found that overall, more female students enrolled in *MVS* courses, but this pattern was reversed in CR enrollments; more male students enrolled for the purpose of credit recovery.

[1] DeBruler, K. (2016). *iEducator 21st Century Digital Learning Core: Program Design and Reflection*. Lansing, MI: Michigan Virtual University. Retrieved from http://media.mivu.org/institute/pdf/iEd_1.pdf.

Table 2. Enrollments Status of 2015-16 Academic Year

Academic Period	# of Enrollments	# of Students	Gender Gap in Total Enrollments	Gender Gap in CR Enrollments
Fall Semester	9,006	7,673	Female 60%	Male 60%
Trimester 1	853	772	Female 62%	N/A 50%
Spring Semester	9,747	8,125	Female 61%	Male 60%
Trimester 2	1,308	1,185	Female 63%	N/A 50%
Trimester 3	1,092	945	Female 62%	Male 74%
Summer Semester	2,431	1,803	Female 50%	Male 56%

Note: The fall period included Fall Semester and Trimester 1. The spring period included Spring Semester, Trimester 2 and Trimester 3. Summer only included Summer Semester.

MVS student information data was collected based on self-reports, so demographical data or variables, e.g., gender or IEP designation, may have been missing or misreported; therefore the data suffered from lack of credibility. The author excluded missing cases from this analysis and, accordingly, the results need to be interpreted with this caveat. Table 3 shows that most students took high school level courses, in general, and also particularly for the reason of credit recovery. With regard to locale codes of students (Table 4), the majority of enrollments came from students in rural or suburban areas. Some notable patterns include the different proportion of “city” or “rural” enrollments out of total enrollments versus out of the CR enrollments. A considerable increase in the proportion of rural or city locale codes occurred in CR enrollments. When it comes to special education eligibility (Table 5), a greater proportion of students holding Individualized Education Plans (IEPs) was found in available data from the CR enrollment sample than from the entire enrollment sample. Due to the data’s lack of credibility those factors were not included in the main analysis for the last research question on performance evaluation.

Table 3. Grade Level Factors

Grade Level	% of Enrollments	% of CR Enrollments
Prior to Secondary	1.8%	0.1%
High School	98.3%	99.9%

Note: Total enrollments with grade level were 24,437 and 763 credit recovery enrollments.

Table 4. Locale Factors

Locale	% of Enrollments	% of CR Enrollments
City	6%	18%
Rural	34%	40%
Suburb	39%	33%
Town	21%	9%

Note: Total enrollments with locale data was 21,592 (11.6% missing data). There were 364 credit recovery enrollments with locale data (52% missing data).

Table 5. IEP Factor

IEP	% of Enrollments	% of CR Enrollments
Has IEP	5.4%	12.5%

Note: Total enrollments with IEP data was 8,583 (66% missing data). There were 369 credit recovery enrollments with IEP data (52% missing data).

Highest CR Enrollment Courses from the Full Sample Data Exploration

Among various courses *MVS* offered (224 types when referring to course titles), the ten highest enrollment courses are listed in Table 6 and Table 7. This analysis suggests that mathematics courses were most frequently taken by CR students throughout the entire school year.

Table 6. Highest Enrollment Courses – All Enrollments

	Fall	Spring	Summer
1	American Sign Language 1 (A)	American Sign Language 1 (B)	Economics
2	Medical Terminology	Study Skills	Health
3	Personal Finance (A)	Medical Terminology	Civics
4	Study Skills	Personal Finance (B)	Algebra 2 (B)
5	German 1 (A)	Economics	Algebra 1 (B)
6	Forensic Science - Introduction	American Sign Language 1 (A)	Algebra 1 (A)
7	Psychology	Health	Algebra 2 (A)
8	Japanese 1 (A)	Business Ethics	Geometry (B)
9	AP Psychology	Personal Finance (A)	Geometry (A)
10	Civics	Careers - Find Your Future	Personal Fitness

Table 7. Highest Enrollment Courses – Credit Recovery Only

	Yearly Credit Recovery Enrollment
1	Algebra 2 (B)
2	Algebra 1 (B)
3	Algebra 2 (A)
4	Algebra 1 (A)
5	English 9 (B)
6	Geometry (B)
7	U.S. History & Geography (A)
8	Geometry (A)
9	English 9 (A)
10	Civics

Course Completion Status from Full Sample Data

There are four types of course completion statuses in the data, including "Audited," "Completed/Passed," "Completed/Failed," and "Withdrawn/Exited." "Completed" was defined as enrollments that remained in class until the last day of the academic term and "Passed" was defined as enrollments that earned at least 60% of the course points. Accordingly, only "Completed/Passed" signifies students who earned a passing grade in the *MVS* course.

Based on those definitions, Table 8 reports two types of performance calculation, including completion rate and passing rate. First, the completion rate calculation centered on grade-attempting enrollments by excluding records listed as "Audited," with 99% for the total enrollments and 98% for the CR enrollments. As a course success indicator, the passing rate was calculated by the percentage of grade-attempting enrollments that earned at least 60% of the course points. The general passing rate was 85%, while the passing rate for CR enrollments dropped to 62%.

Table 8. Course Completion Status by Enrollment Reasons

Status	Course Unavailable	Credit Recovery	Learning Preference	Schedule Conflicts	Other	Total
Audited	45	1	7	41	33	127
Withdrawn/ Exited	99	17	103	29	77	325
Completed/ Failed	1,385	270	755	262	698	3,370
Completed/ Passed	9,918	475	4,162	2,281	3,779	20,615
Completion Rate	99%	98%	98%	99%	98%	99%
Passing Rate	87%	62%	83%	89%	83%	85%

Summary of Final Data Based on Units of Enrollment, Student, and Instructor

As described earlier, the final data set includes only credit-attempting enrollments, as records for audit were excluded. Table 9 and Table 10 depict case distributions reflecting students' enrollment patterns. During the fall academic term, 87.5% of 8,369 students took one course, and 10.3% took two courses, while 87.8% of students worked with one instructor. During the spring term, 82.6% of 9,799 students took one course, and 14% took two courses, while 83.5% of students worked with one instructor. For the summer semester, the number of students who took more than one course increased to approximately 30% of 1,749 students who took summer courses.

Table 9. Summary of Students per Enrollment Period by Number of Enrollments per Student

# of Enrollments Per Student	# of Students (Fall)	% of Students (Fall)	# of Students (Spring)	% of Students (Spring)	# of Students (Summer)	% of Students (Summer)
1	7,323	87.5%	8,094	82.6%	1,220	69.8%
2	860	10.3%	1,369	14.0%	468	26.8%
3	87	1.0%	174	1.8%	36	2.1%
4	37	0.4%	87	0.9%	20	1.1%
5	27	0.3%	30	0.3%	1	0.1%
6	30	0.4%	36	0.4%	4	0.2%
7	4	0.1%	6	0.1%	-	-
8	1	0%	3	0.0%	-	-

Table 10. Summary of Students per Enrollment Period by Number of Instructors per Student

# of Instructors Per Student	# of Students (Fall)	% of Students (Fall)	# of Students (Spring)	% of Students (Spring)	# of Students (Summer)	% of Students (Summer)
1	7,344	87.8%	8,185	83.5%	1,269	72.6%
2	843	10.1%	1,296	13.2%	427	24.4%
3	85	1.0%	166	1.7%	39	2.2%
4	35	0.4%	79	0.8%	9	0.5%
5	33	0.4%	32	0.3%	2	0.1%
6	25	0.3%	32	0.3%	3	0.2%
7	3	0%	8	0.1%	-	-
8	1	0%	1	0%	-	-

Notably, due to the multiple enrollment cases from the same students and the same instructors, the results are slightly different between the numbers of enrollments and instructors per student. For example, the number of students who had only one instructor is greater than the number of students who took only one course, which indicates that some students enrolled in multiple courses that were taught by the same instructor. An example of those cases includes scenarios in which students enrolled in related subjects that were taught by the same instructor. Examples of such combinations include Civics and U.S History/Geography, Latin 2A and Latin 2B, and Introduction to Computer Programming and Game Design.

Exploring distributions of teaching assignments to instructors and teacher assignments to individual students helps us understand contextual information in evaluating the performance of two key actors in online teaching and learning: students and instructors. Figure 3 and Figure 4 present this information by displaying distributions of both enrollment and students per instructor.

The bar graphs display counts of instructors using the vertical axis on the left side, and a dotted line graph presents cumulative counts of instructors from the vertical axis on the right side, while the number of enrollments per instructor are shown on the horizontal axis for both types of charts. Out of 173 instructors, 80% shouldered a teaching load ranging from six to 70 enrollments during the fall term. The most frequently found distribution of teaching assignments was 12 or 38 enrollments: one set of six instructors had 12 enrollments, and another set of six instructors had 38 enrollments. The second most frequently observed enrollment pattern per instructor was four sets of five instructors with 25, 34, 48, and 69 enrollments per instructor. Approximately a tenth of instructors (12%) show a relatively heavy teaching load, with enrollments ranging from 121 to 227. The graphical analyses based on the number of students per instructor share common features with slightly different figures due to cases of multiple enrollments from the same student and instructor. For the spring period, the distribution of students per instructor suggests that 80% of the total 182 instructors shouldered a teaching load ranging from nine to 97 students per instructor. The observation of teaching assignment patterns reveals that eight instructors fall under the instance of 69 per instructor. Twenty instructors carried relatively heavy student loads ranging from 121 to 227.

A distinctive characteristic of the distribution in the summer semester is the plateau after a sharp increase in the graphs of cumulative counts. For example, in the fall period, the plateau seems to start at 73 on the enrollments-per-instructor scale, and thus variations that occurred on cases from 89 through 235 are for 28 instructors. For the spring period, a similar plateau is found with variations occurring from 89 through 235 for 29 instructors. Out of 82 instructors, 82% shouldered a teaching load ranging from five to 68 enrollments per instructor during the summer semester.

Figure 3. Frequency Distributions of Enrollments Based on Instructor

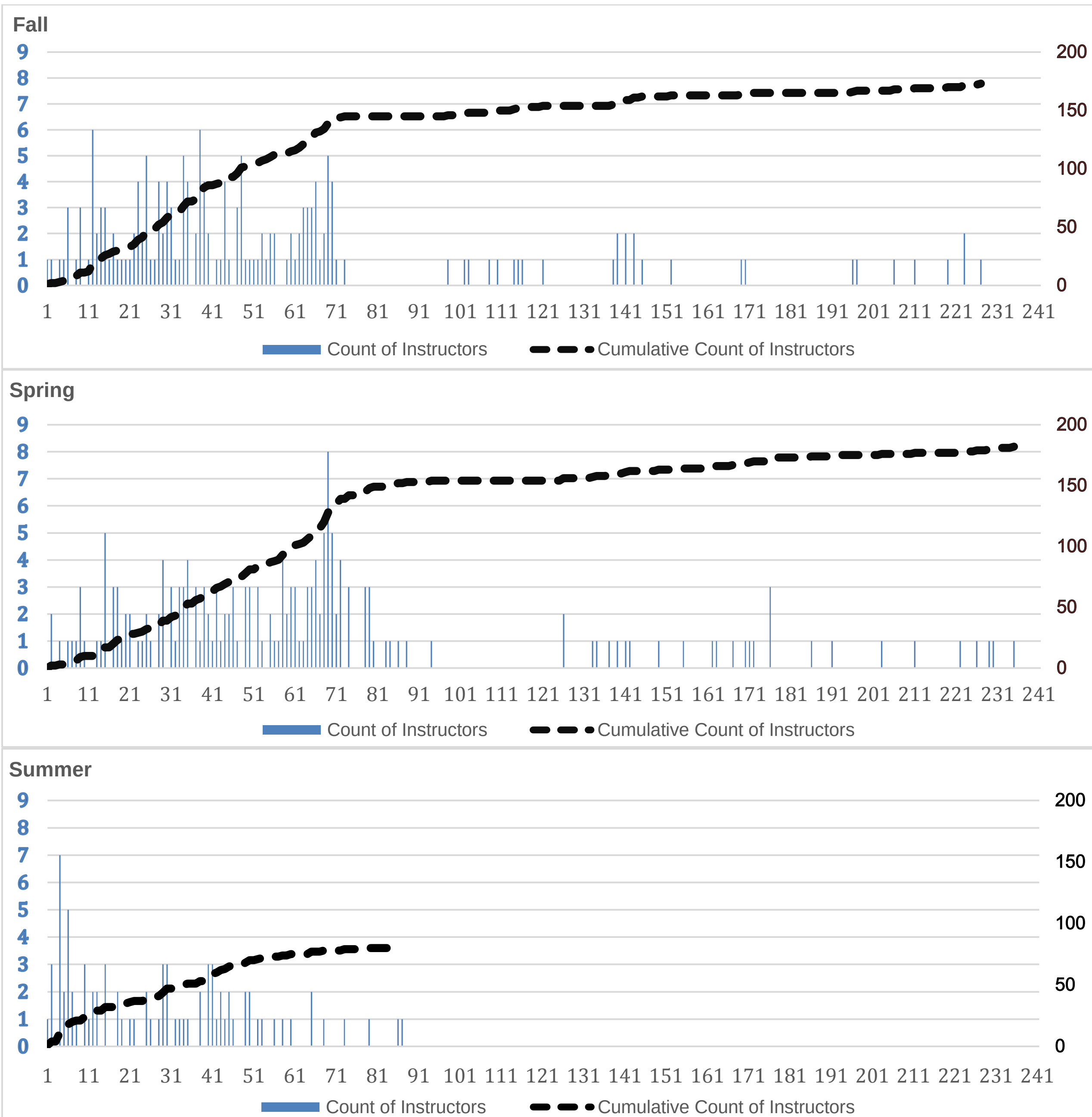
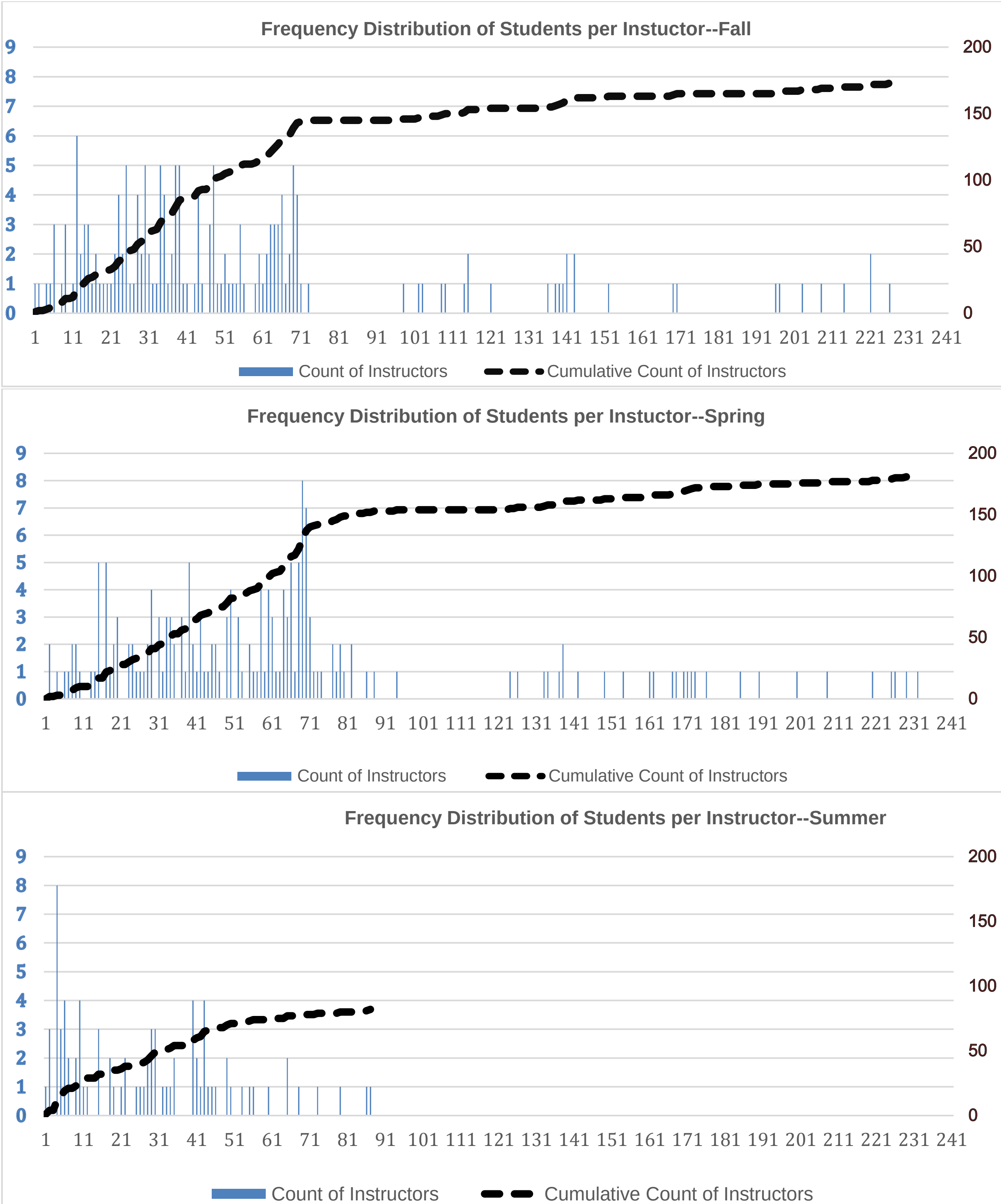


Figure 4. Frequency Distributions of Students Based on Instructor



To approach the data from a slightly different angle, enrollment patterns by degree of teaching load were explored. Using the quartile range of instructor teaching loads, we grouped enrollment records into four groups of enrollments taught by instructors who had (a) a very low teaching load (cut-off at the 25th percentile); (b) a low teaching load (50th percentile); (c) a high teaching load (75% percentile); and (d) a very high teaching load. Those enrollments parceled out by their corresponding instructor teaching loads were examined by enrollment reasons, in order to probe whether or not CR enrollments were associated with instructors whose caseloads were relatively heavy. As shown in Table 11, the proportion of CR enrollments is relatively greater in the group of teachers whose teaching loads were very heavy across three academic terms.

Table 11. CR Enrollment Pattern by Instructor Case Load

Instructor Load	Total Enrolls Fall	% CR[1] Fall	Total Enrolls Spring	% CR Spring	Total Enrolls Summer	% CR Summer
Very Low Teaching Load	573	< 1.5%[2]	794	< 1.6%	89	16.9%
Low Teaching Load	1,474	< 1.5%	1,989	< 1.6%	318	17.0%
High Teaching Load	2,211	< 1.5%	3,007	< 1.6%	700	17.9%
Very High Teaching Load	5,545	2.1%	6,344	2.1%	1,266	18.3%

Notes: 1. CR proportion refers to the proportion of CR enrollments to the total enrollments within each category of instructor teaching load degree. 2. If cell suppression was necessary, the average CR proportion of each academic term was used.

Enrollment patterns were explored using the variable of instructors' position types, including lead instructor, full-time instructor, part-time instructor, and iEducator. According to Table 12, the average caseload was 141 enrollments for lead instructors, 194 for full-time instructors, and 120 for iEducators. For each of these categories, the proportion of CR enrollments is greater than the average CR proportion of total enrollments (1.46%) during the fall period. That is, part-time instructors were assigned fewer CR enrollments than were full-time instructors or iEducators. When it comes to the spring academic term, full-time instructors taught 173 enrollments on average; among them, 2.1% were CR enrollments, while individual iEducators shouldered 165 enrollments with CR enrollments of 2.46%. Fewer CR enrollments were assigned to part-time instructors during the spring academic term. Data from summer semester reflects the increased CR proportion in each instructor-type category, but shared a similar feature of fewer CR enrollments assigned to part-time instructors. There was no deliberate practice of *MVS* to assign one teacher over another. One plausible explanation is that if CR enrollments tended to occur in the early period of enrollment, instructors other than part-time were more likely to receive them as most *MVS* courses had full-time instructors assigned and they were more likely to be placed in the first section of a given course. Note that the caseload reported here would not agree with the actual load of individual instructors because some of them shouldered cases placed in the "Multiple" category for the instructor position type.

Table 12. Case Load Pattern by Instructor Position Type

		Position Type					
		Lead	Full Time	Part Time	iEducator	Multiple	Total
Fall	**Instructor**	6	10	132	13	12	173
	Average Case Load	141	194	38	120	34	57
	CR proportion[1]	2.6%	1.9%	<1.5%[2]	3.4%	< 1.5%	1.5%
Spring	**Instructor**	6	11	136	13	16	182
	Average Case Load	142	173	50	165	29	67
	CR proportion	< 1.6%	2.1%	< 1.6%	2.5%	1.8%	1.6%
Summer	**Instructor**	5	9	52	12	4	82
	Average Case Load	46	51	19	45	43	29
	CR proportion	19.6%	21.2%	14.6%	18.9%	22.7%	17.9%

Notes: 1. CR proportion refers to the proportion of CR enrollments to the total enrollments within each category of instructor position types. 2. If cell suppression was necessary, the average CR proportion of each academic term was used.

Learning Outcomes by Key Factors from the Descriptive Analysis of the Final Data Set

Data on students' final grades were explored in order to examine different learning outcomes by key factors (Table 13 ~ Table 19). Descriptive results suggest the greater group mean scores for the female student group in gender, schedule conflict as the enrollment reason, enrollments taught by lead instructor, and CR enrollments taught by full-time instructors during the fall academic term. The average final grade for the fall academic term was 80 (Std. Dev. 24). When it comes to the spring period, with the average final grade 78 (Std. Dev. 24), we found descriptively higher scores from the female student group in gender, unavailable courses as the enrollment reason, and both general and CR enrollments taught by lead instructor, respectively. Summer data also indicates a similar pattern for the female group who selected "schedule conflicts" as the reason for enrolling in their courses: both general and CR enrollments were taught by lead instructors.

The analysis by teaching load groups appears to suggest the greater group mean for enrollments whose instructors' teaching load was consistently relatively high across three academic terms. Note that in each academic term's data set, the "high" teaching load group was specified based on their respective ranges from the second and third quartiles: the high teaching load is 42–65 enrollments per instructor for the fall period, 58-71 for the spring period, and 28-42 for the summer period. Unlike the performance pattern from the entire sample, no noticeable pattern was found in the performance of CR enrollments across teaching load groups.

Table 13. Descriptive Results of Final Grade by Gender

	Fall			Spring			Summer		
Gender	**Obs.**	**Mean**	**Std. Dev.**	**Obs.**	**Mean**	**Std. Dev.**	**Obs.**	**Mean**	**Std. Dev.**
Female	5,701	80	24	7,399	80	23	1,189	80	27
Male	3,875	76	25	4,735	75	26	1,184	76	28

Table 14. Descriptive Results of Final Grade by Locale

	Fall			Spring			Summer		
Locales	**Obs.**	**Mean**	**Std. Dev.**	**Obs.**	**Mean**	**Std. Dev.**	**Obs.**	**Mean**	**Std. Dev.**
City	603	79	23	707	81	20	52	68	32
Suburban	2,998	78	24	4,209	76	26	1,014	81	25
Town	2,117	81	20	2,357	81	22	57	77	27
Rural	3,211	76	27	3,924	77	25	61	71	32

Table 15. Descriptive Results of Final Grade by Enrollment Reason

	Fall			Spring			Summer		
Enrollment Reason	**Obs.**	**Mean**	**Std. Dev.**	**Obs.**	**Mean**	**Std. Dev.**	**Obs.**	**Mean**	**Std. Dev.**
Course Unavailable	5,181	79	22	6,076	80	22	94	79	28
Credit Recovery	139	47	33	194	57	32	425	62	31
Learning Preference	1,744	76	27	2,519	76	26	726	83	24
Schedule Conflicts	1,087	80	22	1,200	79	21	267	87	20
Other	1,515	77	26	2,145	76	27	861	78	27

Table 16. Descriptive Results of Final Grade by Instructor Type

	Fall			Spring			Summer		
Position Type	**Obs.**	**Mean**	**Std. Dev.**	**Obs.**	**Mean**	**Std. Dev.**	**Obs.**	**Mean**	**Std. Dev.**
Lead	832	80	24	851	80	23	230	80	26
Full time	1,913	78	24	1,901	76	25	455	74	31
Part time	4,984	78	25	6,783	78	24	975	79	27
iEducator	1,531	76	25	2,143	77	25	541	80	25
Multiple	406	77	23	456	79	24	172	74	30

Table 17. Descriptive Results of Final Grade by Teaching Load Group

	Fall			Spring			Summer		
Load Group	**Obs.**	**Mean**	**Std. Dev.**	**Obs.**	**Mean**	**Std. Dev.**	**Obs.**	**Mean**	**Std. Dev.**
Very Low	573	76	26	794	79	24	89	73	31
Low	1474	78	24	1989	76	25	318	73	32
High	2211	79	24	3007	80	23	700	80	26
Very High	5545	78	24	6344	77	25	1266	78	27

Table 18. Descriptive Results of CR Final Grade by Four Position Types

	Fall			Spring			Summer		
Position Type	**Obs.**	**Mean**	**Std. Dev.**	**Obs.**	**Mean**	**Std. Dev.**	**Obs.**	**Mean**	**Std. Dev.**
Lead	22	47	34	13	69	30	45	67	29
Full time	37	51	32	39	59	30	97	64	31
Part time	30	35	34	81	58	31	142	59	34
iEducator	53	50	32	53	53	33	102	66	28

Table 19. Descriptive Results of CR Final Grade by Teaching Load Groups

	Fall			Spring			Summer		
Load Group	**Obs.**	**Mean**	**Std. Dev.**	**Obs.**	**Mean**	**Std. Dev.**	**Obs.**	**Mean**	**Std. Dev.**
Very Low	<10	47	37	11	44	38	15	45	38
Low	11	36	32	22	62	32	54	55	35
High	<10	42	40	27	56	32	125	64	30
Very High	118	48	33	134	57	31	231	64	30

Statistical Evidence on CR Enrollments' Underperformance

Table 20 and Table 21 summarizes the result of key actors' performances by regressing students' final grades on various enrollment-, student-, and instructor-level factors that were available from the credible data. Cross-classified multilevel modeling was used to address the unique features of the data. The gender variable is a comparison of the female students' outcomes with their male counterparts' outcomes so that the positive symbol in the table indicates that the female students significantly outperformed their male counterparts. The enrollment-reason variable is dummy-coded, which allows for comparison between one of the enrollment-reason categories and all other categories. For example, "Course Unavailable" is a significant factor in a positive direction, so that students with the enrollment reason that the course was not available at their local school significantly outperformed in comparison with students who had all other types of enrollment reasons. "Non-sig." denotes that there is no significant association between the introduced predictor and student outcomes statistically.

From various modeling results, a consistent pattern emerged: enrollments for credit recovery show a significant underperformance. Students who enrolled for courses because the courses were not available at local schools or because the students had schedule conflict were most likely to outperform those who indicated all any other reason; but the statistical results changed depending on what other dummy variables were introduced. When all of the three representative underperforming groups including the credit recovery group, the learning preference group, and the "other reasons" group are introduced to the model, the statistical significance of the course-unavailable group or the schedule-conflict group could disappear. Another key factor is gender, since the data show that female students are more likely to succeed in online courses. The full model, after including the variable of instructor type, found that there was no statistically significant difference in student outcomes between instructors' different position types, suggesting successful instructor-resource deployment by *MVS*. This pattern is consistent across three academic terms.

Table 20. Cross-Classified Multi-Level Modeling Results for Enrollment and Student Model

	Statistical Conclusion		
Variable	**Fall**	**Spring**	**Summer**
Female	+	+	Non-sig.
Course Unavailable	+	+	Non-sig.
Credit Recovery	-	-	-
Learning Preference	Non-sig.	Non-sig.	Non-sig.
Schedule Conflict	+	+	+
Female	+	+	Non-sig.
Course Unavailable	Non-sig.	Non-sig.	Non-sig.
Credit Recovery	-	-	-
Learning Preference	-	-	Non-sig.
Other Reason	-	-	-

Note: In the enrollment and student model, gender and enrollment reason variables were introduced. Research Question - Is there any significant student-level factor that is associated with final grade scores while controlling for the unique structure of data—enrollments are nested in student- and instructor-level variable, respectively?

Table 21. Cross-Classified Multi-Level Modeling Results for Full Model

	Statistical Conclusion		
Variable	**Fall**	**Spring**	**Summer**
Female	+	+	Non-sig.
Course Unavailable	+	+	Non-sig.
Credit Recovery	-	-	-
Learning Preference	Non-sig.	Non-sig.	Non-sig.
Schedule Conflict	+	+	+
Full-time Instructor	Non-sig.	Non-sig.	Non-sig.
Part-time Instructor	Non-sig.	Non-sig.	Non-sig.
iEducator	Non-sig.	Non-sig.	Non-sig.
Multiple Instructors	Non-sig.	Non-sig.	Non-sig.
Female	+	+	Non-sig.
Course Unavailable	+	+	Non-sig.
Credit Recovery	-	-	-
Learning Preference	Non-sig.	Non-sig.	Non-sig.
Schedule Conflict	+	+	+
Full-time Instructor	Non-sig.	Non-sig.	Non-sig.
Part-time Instructor	Non-sig.	Non-sig.	Non-sig.
iEducator	Non-sig.	Non-sig.	Non-sig.
Lead Instructor	Non-sig.	Non-sig.	Non-sig.
Female	+	+	Non-sig.
Course Unavailable	Non-sig.	Non-sig.	Non-sig.
Credit Recovery	-	-	-
Learning Preference	-	-	Non-sig.
Other Reason	-	-	-
Full-time Instructor	Non-sig.	Non-sig.	Non-sig.
Part-time Instructor	Non-sig.	Non-sig.	Non-sig.
iEducator	Non-sig.	Non-sig.	Non-sig.
Multiple Instructors	Non-sig.	Non-sig.	Non-sig.
Female	+	+	Non-sig.
Course Unavailable	Non-sig.	Non-sig.	Non-sig.
Credit Recovery	-	-	-
Learning Preference	-	-	Non-sig.
Other Reason	-	-	-
Full-time Instructor	Non-sig.	Non-sig.	Non-sig.
Part-time Instructor	Non-sig.	Non-sig.	Non-sig.
iEducator	Non-sig.	Non-sig.	Non-sig.
Lead Instructor	Non-sig.	Non-sig.	Non-sig.

Note: In the full model, instructor-level variables – instructor type, were introduced concurrently. Research Question: Is there any significant factor that is associated with final grade scores while controlling for the data structure as well as any covariance due to other factors?

Discussion

As state virtual schools play a pivotal role in offering credit recovery options, stakeholders need more information from various research and evaluation efforts around the topics of CR enrollments and their performance. Key findings from this report will frame stakeholders' discussions about the strengths and areas for improvements in online CR programs.

More students enrolled in MVS mathematics courses and summer courses for credit recovery. Algebra courses accounted for the largest share of credit recovery enrollments during the 2015-16 academic year. For this high-needs course, the content delivery structure and/or student support system needs to be examined from the perspective of CR. This suggests that approximately one-fifth of summer enrollments are from students in need of credit recovery, and with this context, launching special summer credit recovery programs also deserves earnest consideration. If those programs are going to be developed, various topics need to be discussed, for example, Algebra courses tailored to CR students' needs to balance between remediation and rigor in the course content and to embed a variety of practices that support low-performing students' active participation and successful learning (Bakia et al., 2013). Furthermore, ongoing and longitudinal evaluation and research efforts should be developed as a part of CR programs. In framing this evaluation and research, it is important to take a comprehensive view by collecting data on short-term outcomes (e.g., passing rate), long-term outcomes (e.g., graduation rate), and various types of contextual information (e.g., additional supports that students receive from family or schools they attend).

Findings and study limitations have implications for practitioners and researchers. First, CR enrollments were more likely to be related to male students, city locale, or rural locale. Notably, descriptive statistics of final grades indicate the low average and high deviations of male students across three academic terms and those of enrollments from rural or city area during fall or summer term. Accordingly, when administrators design and implement a support system for those specific learner groups (e.g., students in rural areas), they can take a proactive approach by embedding practices from which struggling learners also can benefit.

The second type of factor, which is more likely to relate to CR enrollments but not to the underperformance of students, also helps us choose an area of concentration. For example, more CR enrollments were found with instructors whose teaching loads were in the top quarter (i.e., most heavy teaching load groups), but the corresponding examination of their students' performance did not necessarily indicate a systematic low-performing profile across three academic terms. Furthermore, it was revealed that the factor of instructors' position type was not statistically associated with student learning outcomes. It is important to recognize that failure to find a significant association between some set of instructor characteristics and student-learning outcomes does not mean that all instructors have the same effectiveness in promoting student learning under the same circumstance. Average teaching loads were different across instructor types and subject areas based on *MVS* teaching assignment policy and practices. Furthermore, *MVS* instructors were provided with fully designed online courses where they could supplement the course content but were not responsible for devising the curriculum. Accordingly, study findings could be construed as a successful implementation of *MVS* policy and practices pertaining to instructor types and teaching assignment.

However, findings mentioned above could guide future exploration of instructor effects in the K-12 online context, that is, discovering whether it is possible to create variation in effectiveness at the instructor level and how to do so. If we were able to identify any significant variance in student learning outcomes that were associated with variation in measured instructor characteristics, manipulating those factors would function as the mechanism of educational improvement. In this vein, further research may be directed at the quantity and quality of communication between instructors and students and of feedback instructors provided to students, given the importance of those elements of online teaching. On the other hand, students who are taking online courses are supposed to benefit from mentor supports at the school building level; hence researchers need to look closely at the quantity and quality of this type of support, in order to reach a fuller understanding of students' learning and success in online courses.

Finally, the crux of the study findings is statistically significant underperformance of CR enrollments. Even if any variance that would be attributable to gender, instructor types, and data structure are controlled, CR students are more likely to underperform in the online courses. The result highlights that it is important to establish robust support structure in online learning – even more so in the context of remediation than acceleration. This support structure builds upon mutual goals of student success, shared accountability, and shared resources amongst course providers, schools, and districts (Archambault et al., 2015).

There was limited access to data on student information through the state virtual school data system so that confounding effects of individual background on learning outcomes were not removed. The prior achievement data is especially worthy of notice not only because it is the strongest predictor of any form of learning outcomes, but also because it could be regarded as a variable summarizing influences of individual family, school, and/or neighborhood background. The model of current study, however, did not account for the systematic difference in prior achievement between CR reason for enrollment and other reason categories. As such, CR students' underperformance would not be attributable solely to enrollment reasons, but also to the covariance between enrollment reasons and student personal background including academic ability, family supports, and school characteristics they attend. While this limitation underscores the need for improving data collection policy and practices for state virtual schools, it does not necessarily exert influence on reaching a conclusion regarding the importance of robust support structure tailored to CR students based on shared accountabilities of both stakeholders of program providers and schools/districts they attend.

The present study has been guided by Ajzen's Theory of TPB, which encompasses various components related to student learning and success in online courses and helping us understand how we successfully serve students. The study, however, addresses only a small portion of what this theory accounts for: a link between different reasons for course enrollments correlated with learning outcomes. This limitation guides next steps for *MVLRI*'s CR series to take – exploring more fine-grained learning behaviors throughout the course period – from the perspective of the CR enrollment reason. For the next study, a time-series hierarchical clustering analysis will be conducted, in order to investigate patterns that are captured by time-stamped data on student activities and to identify any distinctive learner groups.

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Appendix

Hypotheses from the Perspective of Ajzen's Theory of Planned Behavior

Ajzen's Theory of Planned Behavior (TPB) guided this study. According to TPB, behavioral intention, whose antecedents include *attitude toward the behavior*, *subjective norm*, and *perceived behavioral control*, is indicative of a person's readiness to perform a behavior (Ajzen, 1991; 2006). *Attitude toward the behavior* is a concept concerning an individual's negative or positive perception of performing the behavior. *Subjective norm* is concerned with other key peoples' perceptions of whether or not the individual should perform the behavior. Lastly, *perceived behavioral control* refers to the individual's belief about her/his capability to perform that specific behavior.

In the context of this study concerning students carrying out successful learning behaviors in online courses, Ajzen's Theory was applied to form the hypothesis that CR as a reason for enrollment and student learning outcomes are negatively correlated. That is, what underlies the present study is that in cases of credit recovery, not only students but also key people around them (e.g., school teachers or parents) would have less favorable perceptions about students' capability to set up desired learning goals (e.g., be mastery-oriented rather than avoidance-oriented), to manage specific learning behaviors and actions, and to succeed in online courses. These different beliefs would lead to different behavioral intentions, different engagement levels, and ultimately, different learning outcomes. In that vein, the first part of this CR series is to test whether or not students' performances will be different depending on their reasons for choosing the online courses, while controlling for other key factors and the unique structure of virtual school data.

Model Estimation

Model estimation is presented for the key model that includes gender, four types of predefined enrollment reasons and four types of instructor position types after omitting "other" category of enrollment reasons and "multiple" category of instructor position type from the model to eliminate multicollinearity issue. The cross-classified multi-level modeling were estimated by using Stata14 and presented in classification notation (University of Bristol, 2010).

Unconditional Model

$$Final_i = \beta_0 + u^{(3)}_{instructor(i)} + u^{(2)}_{student(i)} + e_i$$

	Fall		Spring		Summer	
Component	**Est.**	**SE[1]**	**Est.**	**SE**	**Est.**	**SE**
_cons	78.26		77.94		77.32	
Between-Instructor	31.69	4.45	27.42	4.37	82.67	18.81
Between-Student	343.21	8.57	388.21	9.74	370	23.80
Residual Variance	190.71	5.41	152.75	5.74	294.25	16.42
Log Likelihood	-54410.631		-43695.923		-10757.612	

Notes 1. Standard Error.

Adding Enrollment- and Student-level Predictors

$$Final_i = \beta_0 + \beta_1 course_i + \beta_2 credit_i + \beta_3 learning_i + \beta_4 schedule_i + \beta_5 female_i + u^{(3)}_{instructor(i)} + u^{(2)}_{student(i)} + e_i$$

	Fall			Spring			Summer		
Component	**Est.**	**SE**	**Sig. z^2**	**Est.**	**SE**	**Sig. z**	**Est.**	**SE**	**Sig. z**
Course Unavailable	2.94	0.63	4.66	1.68	0.73	2.32	2.13	3.04	
Credit Recovery	-14.47	1.81	-7.99	-28.05	2.07	-13.53	-12.43	1.68	-7.39
Learning Preference	0.01	0.74		0.15	0.86		2.68	1.47	
Schedule Conflicts	2.41	0.86	2.81	2.24	0.94	2.37	5.81	1.97	2.95
Female	4.59	0.48	9.56	4.19	0.52	7.98	1.73	1.18	
_cons	73.88		N/A	74.6		N/A	74.6		N/A
Between-Instructor	30.05	4.27	N/A	27.25	4.3	N/A	58.81	15.02	N/A
Between-Student	331.71	8.43	N/A	366.28	9.44	N/A	333.71	22.72	N/A
Residual Variance	191.06	5.41	N/A	155.03	5.77	N/A	300.85	16.65	N/A

Note:2. Only significant z scores are reported.

The log likelihood estimation is 54302.34 for Fall; -43549.25 for Spring; and -10710.62 for Summer. The Wald $chi^2(3)$ estimation is 219.23 (*Prob* > chi^2 = 0) for Fall; 299.62 (*Prob* > chi^2 = 0) for Spring; and 99.29 (*Prob* > chi^2 = 0) for Summer.

Adding Instructor-level Predictors

$$Final_i = \beta_0 + \beta_1 course_i + \beta_2 credit_i + \beta_3 learning_i + \beta_4 schedule_i + \beta_5 female_i + \beta_6 Full_i + \beta_7 part_i + \beta_8 iEdu_i + \beta_9 lead_i + u^{(3)}_{instructor(i)} + u^{(2)}_{student(i)} + e_i$$

	Fall			Spring			Summer		
Component	**Est.**	**SE**	**Sig. z^2**	**Est.**	**SE**	**Sig. z**	**Est.**	**SE**	**Sig. z**
Course Unavailable	1.7	0.73	2.34	2.93	0.63	4.64	1.93	3.03	
Credit Recovery	-28.09	2.07	-13.54	-14.46	1.81	-7.99	-12.46	1.68	-7.40
Learning Preference	0.15	0.86		0.003	0.74		2.73	1.47	
Schedule Conflicts	2.24	0.94	2.38	2.41	0.86	2.81	5.83	1.97	2.96
Female	4.19	0.52	8	4.59	0.48	9.56	1.7	1.18	
Full-time	2.22	2.61		-4.12	2.51		-3.38	4.83	
Part-time	2.13	2.06		-1.64	1.89		3.17	4.26	
iEducator	2.31	2.5		-1.69	2.4		4.45	4.71	
Lead	4.76	2.98		-0.26	2.95		4.93	5.49	
_cons	72.43		N/A	75.54		N/A	74.86		N/A
Between-Instructor	26.53	4.23	N/A	29.38	4.2	N/A	50.75	13.56	N/A
Between-Student	366.32	9.44	N/A	331.71	8.42	N/A	335.26	22.74	N/A
Residual Variance	155.04	5.77	N/A	191.06	5.41	N/A	300.09	16.59	N/A

The log likelihood estimation is -43547.976 for Fall; -54300.751 for Spring; and -10707.504 for Summer. The Wald $chi^2(3)$ estimation is 302.23 (*Prob* > $chi^2 = 0$) for Fall; 222.58 (*Prob* > $chi^2 = 0$) for Spring; and 107.84 (*Prob* > $chi^2 = 0$) for Summer.

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