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Abstract Title
Online Credit Recovery: Implementation and Initial Impact of a Prevalent Practice

Authors

Jordan Rickles (jrickles@air.org), Rui Yang, Peggy Clements, Iliana Brodziak de los Reyes, and Jessica Heppen

American Institutes for Research

Background
Use of online credit recovery is a growing trend across the country, with the hope that expanding credit recovery options through online courses will help students get back on track toward graduation (e.g., Atkins, Brown, & Hammond, 2007; Gemin, Pape, Vashaw, & Watson, 2015). But expanded use of online credit recovery for high school students has outpaced the research. As concerns mount over how much students learn in online courses and questions arise about how to best implement online credit recovery, there is a critical need for rigorous evidence about the effective use of online credit recovery for high school students (Ferdig, 2010; Schaeffer & Konetes, 2010).

Online courses are delivered in varying formats. Some are fully online and completely self-paced; others are hybrid or blended models that combine online learning with face-to-face teacher support for students (Staker & Horn, 2012; Watson & Ryan, 2006). The promise of online courses for credit recovery lies in features afforded by the technology that, when utilized, can result in courses designed to meet the specific needs of academically at-risk students. These features include diagnostic assessments to "personalize" content to match a student's ability level; simulations, animations, and interactive tools to promote engagement and support learning; lessons that consistently employ evidence-based models for structuring concepts to support learning; and flexibility that allows students to progress through course material at their own pace (Archambault et al., 2010; Bakia et al., 2013; Blackboard K–12, 2009; Dynarski et al, 2008; Mayer, 2011; Mayer & Moreno, 2003; U.S. Department of Education, 2009).

Purpose
We conducted a multisite study to test a blended-learning model for credit recovery, where the main curriculum is provided through an online program and an in-class teacher provides more individualized instructional support. In this paper, we present findings on the implementation and initial outcomes for two cohorts of students who enrolled in an Algebra 1 or English 9 credit recovery course the summer immediately after their first year of high school.

In particular, we address three main research questions to describe how implementation of the online classes differed from the schools' business-as-usual (BAU) teacher-directed approach to credit recovery, and provide preliminary evidence about the short-term effects of the online approach:

RQ1. How did the ***instructional features*** of the online classes compare to the BAU classes?

RQ2. How did ***students' experiences*** in the online classes compare to the BAU classes?

RQ3. How did students' ***proximal outcomes*** (content knowledge and credit recovery) in the online classes compare to the BAU classes?

Intervention

The intervention for this study was an Algebra 1 or English 9 (first or second semester) online curriculum for the credit recovery course, where an online provider supplied the main course content and curriculum, and the school provided the appropriate, credentialed in-class teacher who could supplement the digital instruction. For both the intervention and BAU conditions, students took the class within a standard classroom during the district's 5-week summer session. The BAU classes primarily relied on traditional teacher-directed instruction, where teachers had latitude in the curriculum and instructional materials for the class.

Population and Setting

The analysis is based on 1,737 students in 98 classes across 24 high schools in a large urban district. All students entered 9^{th} grade in the 2017-18 school year (Cohort 1) or the 2018-19 school year (Cohort 2) and failed their Algebra 1 and/or at least one semester of their English 9 course and enrolled in a credit recovery course the summer between their 9^{th} and 10^{th} grade year. Tables A.1 and A.2 present descriptive statistics and baseline equivalence for the Algebra 1 and English 9 student samples, respectively.

Research Design

Students were randomly assigned to take their credit recovery course in an online class (treatment) or a BAU class (control). Random assignment took place within blocks defined by school. In some schools, blocks were further defined by which semesters of the course the students failed during their 9^{th} grade year.

Data Collection and Analysis

In addition to extant district student background and course data, we collected the following data for the study: (1) an end-of-course teacher survey to measure instructional features; (2) an end-of-course student survey to measure student experiences in the course; and (3) a 20-item end-of-course student test to measure Algebra or English content knowledge. The data sources and measures are described in Table A.3.

All analyses were conducted separately for Algebra and English. For RQ1, we estimate average differences in instructional characteristics between the treatment classes and the control classes with regression models that control for school. For RQ2 and RQ3, we estimate average treatment effects for the intent-to-treat student sample using regression models that control for student characteristics and randomization blocks. We will use multiple imputation to account for missing data, including student survey and test non-response.

Findings

Based on preliminary analyses for English Cohort 1, we observed the following key findings:

- The treatment classes had more individualized pacing but less instructional support than the control classes. Treatment teachers also reported feeling less prepared/supported to teach the class than control teachers. (See Figure A.1.)

- When assigning final course grades, teachers in online classes placed more emphasis on tests and quizzes, and less emphasis on class assignments and behavioral criteria. (See Figure A.2).

- The students assigned to the treatment and control classes had similar experiences. (See Figure A.3.)

- Students assigned to the treatment and control classes had similar test scores, but treatment students were less likely to pass the class. (See Figure A.4.)

Conclusions

The findings suggest that implementation of the online classes produced limited instructional contrast with the BAU condition and may have unintentionally altered grading practices. Potentially as a result, fewer students recovered the course credit in the online classes than the control classes. For the full paper, we will expand the analysis to Algebra and Cohort 2. To explore how implementation and outcomes differ across settings and students, we will examine the connection between implementation and outcomes, as well as how outcomes differ across student subgroups, subjects, and cohorts.

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Appendix

Table A.1. Descriptive Statistics and Baseline Equivalence for the Algebra 1 Student Sample (Cohort 2 only)

	Treatment Students		Control Students			
Student Characteristics	*N*	*Mean*	*N*	*Mean*	**SMD**	***p***
Female	310	0.47	303	0.42	0.13	0.071
Eth: Afr. Am. / Black	310	0.10	303	0.13	-0.15	0.611
Eth: Asian/Pac. Isl.	310	0.03	303	0.02	0.07	0.834
Eth: Latinx / Hispanic	310	0.81	303	0.80	0.02	0.606
Eth: Other	310	0.01	303	0.01	-0.44	0.441
Eth: White	310	0.06	303	0.04	0.33	0.066
FRPL eligible	310	0.83	303	0.78	0.19	0.526
Gifted/talented	310	0.06	303	0.08	-0.14	0.651
Student w/ disability	310	0.11	303	0.07	0.31	0.192
ELL (level 4 or 5)	310	0.20	303	0.17	0.15	0.158
Attendance rate (9th grade)	310	0.92	303	0.92	-0.08	0.578
GPA (9th grade)	310	1.49	303	1.60	-0.16	0.372
SB Grade 8 z-score: ELA	268	-0.43	254	-0.36	-0.09	0.967
SB Grade 8 z-score: Math	271	-0.52	251	-0.42	-0.14	0.240

Notes: ELL = English language learner; FRPL = Free/reduced price lunch; SB = Smarter Balanced (standardized based on districtwide mean and standard deviation); SMD = standardized mean difference. The SMD was calculated using the Cox index for dichotomous measures and Hedge's g for continuous measures. The p-value is based on a logistic regression for dichotomous measures and a linear regression for continuous measures, controlling for randomization blocks.

Table A.2. Descriptive Statistics and Baseline Equivalence for the English 9 Student Sample (Cohorts 1 and 2)

	Treatment Students		Control Students			
Student Characteristics	*N*	*Mean*	*N*	*Mean*	**SMD**	***p***
Female	564	0.35	560	0.33	0.04	0.782
Eth: Afr. Am. / Black	564	0.08	560	0.09	-0.06	0.771
Eth: Asian/Pac. Isl.	564	0.03	560	0.03	0.00	0.792
Eth: Latinx / Hispanic	564	0.85	560	0.83	0.09	0.516
Eth: Other	564	0.01	560	0.01	-0.32	0.331
Eth: White	564	0.04	560	0.05	-0.13	0.904
FRPL eligible	564	0.89	560	0.90	-0.04	0.414
Gifted/talented	564	0.12	560	0.12	0.02	0.836
Student w/ disability	564	0.11	560	0.13	-0.10	0.227
ELL (level 4 or 5)	564	0.15	560	0.16	-0.06	0.642
Attendance rate (9th grade)	564	0.85	560	0.84	0.04	0.389
GPA (9th grade)	564	1.37	558	1.34	0.03	0.200
SB Grade 8 z-score: ELA	492	-0.46	485	-0.47	0.01	0.491
SB Grade 8 z-score: Math	493	-0.44	485	-0.38	-0.08	0.265

Notes: ELL = English language learner; FRPL = Free/reduced price lunch; SB = Smarter Balanced (standardized based on districtwide mean and standard deviation); SMD = standardized mean difference. The SMD was calculated using the Cox index for dichotomous measures and Hedge's g for continuous measures. The p-value is based on a logistic regression for dichotomous measures and a linear regression for continuous measures, controlling for randomization blocks.

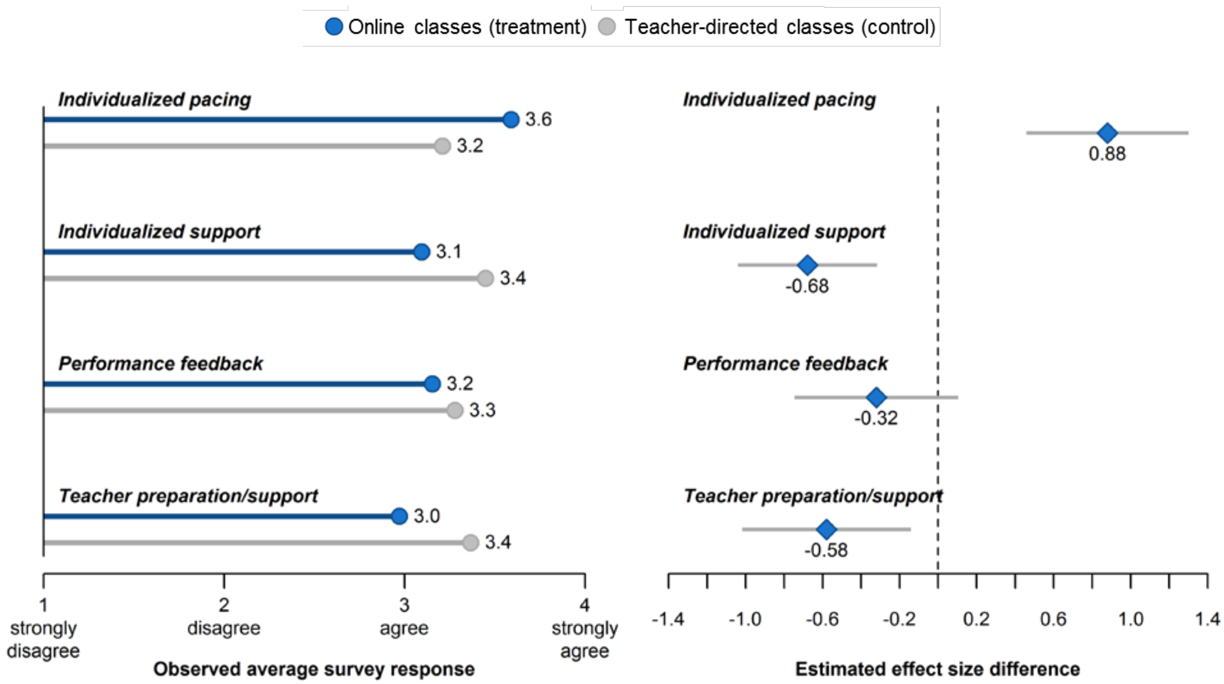
Table A.3. Summary of data sources and measures

Data Source	Measures
District extant data	*Student background characteristics and prior academic performance* See characteristics listed in Table A.1
District extant data	*Passed credit recovery class* Dichotomous measure based on the student's grade in the summer credit recovery class: 1 = grade of D or better; 0 = grade of F, incomplete, or no grade
Teacher survey	*Individualized pacing* A scale[a] of 5 Likert-type survey items about a teacher's level of agreement to statements such as the following: • Different students work on different topics or skills at the same time. • Students can work through instructional material at a faster or slower pace than other students in this class.
Teacher survey	*Instructional support* A scale[a] of 6 Likert-type survey items about a teacher's level of agreement to statements such as the following: • Various materials or instructional approaches are available to accommodate individual student needs or interests. • If students have trouble understanding material, they can get help quickly.
Teacher survey	*Performance feedback* A scale[a] of 4 Likert-type survey items about a teacher's level of agreement to statements such as the following: • Students receive immediate feedback on problem solutions. • Students keep track of their own learning progress.
Teacher survey	*Teacher preparation/support* A scale[a] of 5 Likert-type survey items about a teacher's level of agreement to statements such as the following: • I felt well prepared to teach this class. • I had the necessary support from peers or leaders to teach this class.
Student survey	*Engagement* Two scales of 5 Likert-type survey items each: one about a student's behavioral engagement and one about a student's emotional engagement. Based on level of agreement to statements such as the following: • (Behavioral) I try hard to do well in this class. • (Emotional) When we work on something in class, I feel interested.
Student survey	*Personalism* A scale of 5 Likert-type survey items about a student's level of agreement to statements such as the following: • My teacher helped me catch up if I was behind. • My teacher noticed whether I had trouble learning something.

Data Source	Measures
Student survey	*Academic press* A scale of 4 Likert-type survey items about a student's level of agreement to statements such as the following: • I found the work challenging. • The assignments often required me to explain my answers.
Student survey	*Clarity of class expectations* A scale of 7 Likert-type survey items about a student's level of agreement to statements such as the following: • It was clear what I needed to do to get a good grade in this class. • I learned a lot from feedback on my work in class.
Student test	*Algebra 1 or English 9 content knowledge* IRT-based scale score for a 20-item multiple-choice test developed by the study team and administered during the last week of the summer session.

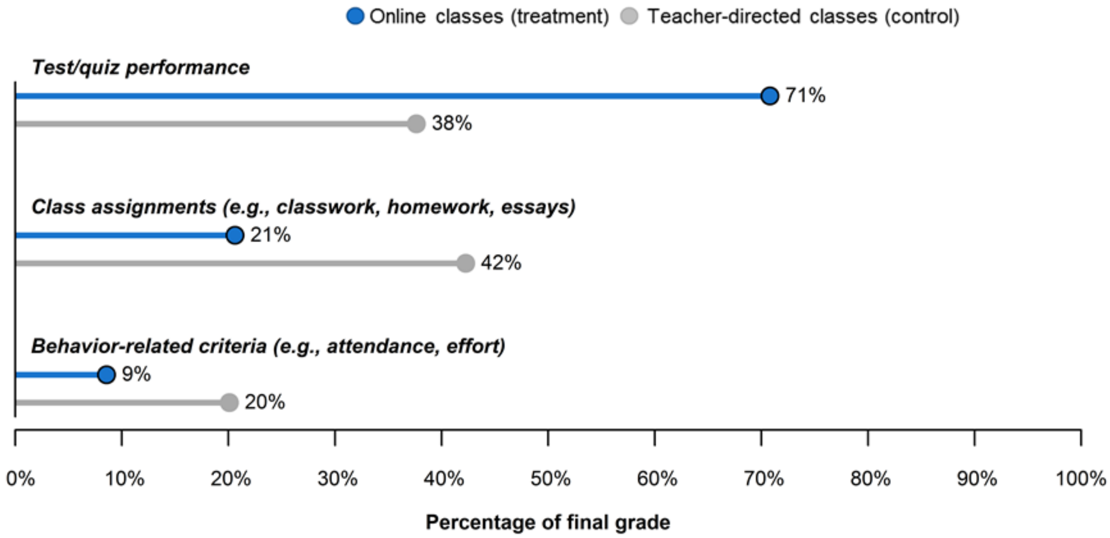
a. For the preliminary analysis, we used the average response across the survey items as the measure. For the final analysis, we will use factor scores.

Figure A.1. Differences in the treatment and control classes' instructional features (Preliminary)



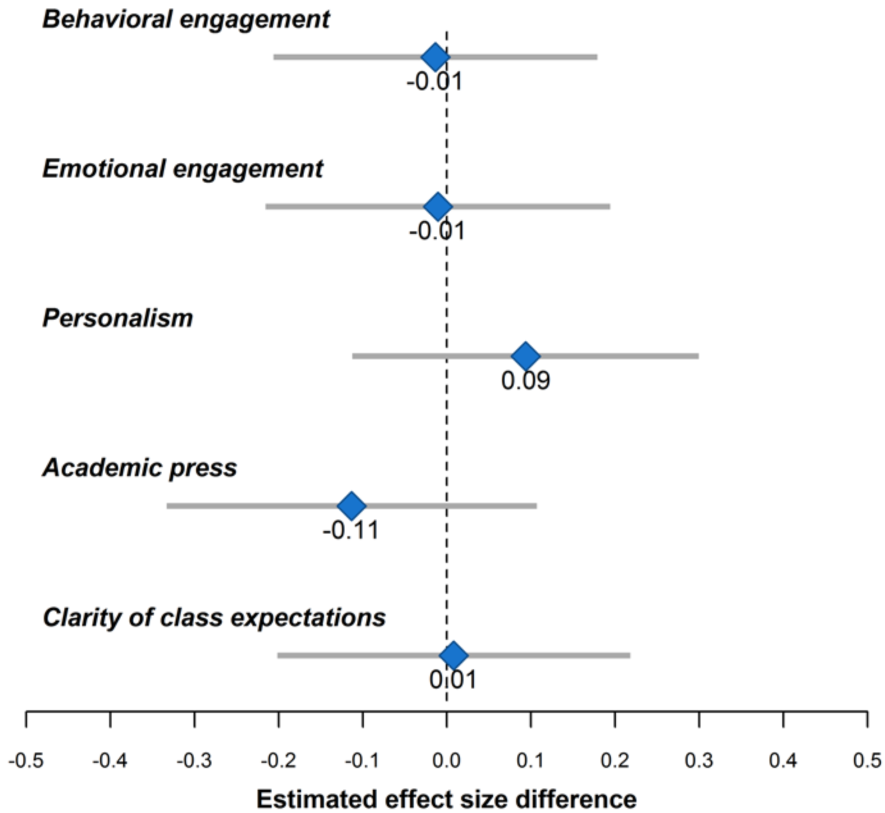
Notes. Preliminary results are based on teacher survey responses for the summer 2018 term. The final analysis will include teachers from the summer 2018 and summer 2019 terms. The left figure reports the average response across teacher survey responses for each feature. The right figure reports the effect size point estimates and the 95% confidence intervals. Effect sizes were calculated using Hedge's *g*. *N* = 42 classes.

Figure A.2. Teachers' emphasis on different grading criteria for students' final course grade (Preliminary)



Notes. Preliminary results are based on teacher survey responses for the summer 2018 term. The final analysis will include teachers from the summer 2018 and summer 2019 terms. Reported percentages are based on average teacher responses to a survey question that asked teachers to report the percentage of the final grade they based on different grading criteria. $N = 42$ classes.

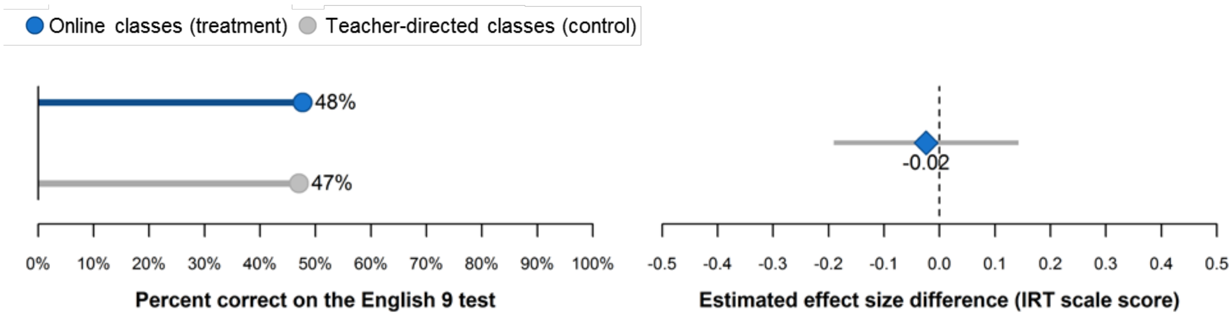
Figure A.3. Differences in treatment and control students' instructional experiences (Preliminary)



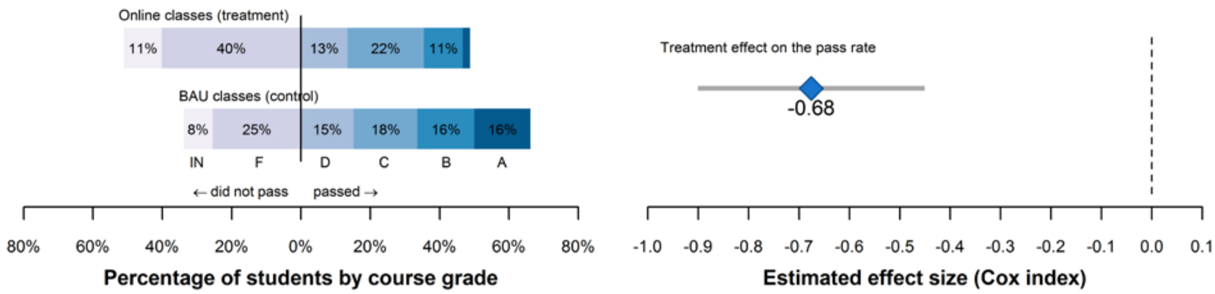
Notes. Preliminary results are based on student survey responses for the summer 2018 term. Final analysis will include students from the summer 2018 and summer 2019. The results are based on a covariate-adjusted regression model with block fixed effects. The effect size point estimates are represented by diamonds and the 95% confidence intervals are represented by horizontal grey bars. N = 464 students.

Figure A.4. Differences in treatment and control students' proximal outcomes

Student Test Performance



Student Final Grade



Notes. Top panels show the average percent correct and average effect on the student test, respectively. *N* = 452 students for the summer 2018 term. Bottom panels show the observed distribution of course grades and the everage effect on the pass rate, respectively. *N* = 789 students for the summer 2018 term. Estimated effects are based on a linear model (for test score) or logistic model (for pass rate) that accounts for student background characteristics and block fixed effects. Final analysis will include students from the summer 2018 and summer 2019.