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ALT-Placement Project: Investigating Adaptive Learning Tools for Mathematics Remediation and Placement

Executive Summary of the Final Narrative Report to the Kresge Foundation, April 30, 2019

Only 28 percent of students enrolled in developmental courses will complete their degrees (Attewell, Lavin, Domina, & Levey, 2006). For most, placement into developmental math courses is determined by their score on a one-time, high-stakes exam taken shortly after being admitted to college. Increasingly, researchers have questioned the validity of these exams and the developmental course "treatment" that is required based on the outcomes of those tests (Medhanie et al., 2012; Melguizo et al., 2014).

In Fall 2017, the Kirwan Center received a $150,000 Phase I planning grant from the Kresge Foundation to explore the efficacy and feasibility of replacing the high-stakes mathematics placement exam process with a process that, instead, *empowers* students to assess and develop their mathematics knowledge using adaptive learning tools made available to them prior to matriculation. We believe these adaptive learning tools can deliver just-in-time skills remediation while also providing more reliable diagnostics of students' knowledge, facilitating more accurate math course placements that will increase student success and lower costs by reducing the number of required non-credit developmental courses.

Goal: The primary goal of this project was to see if adaptive learning tools hold promise to: 1) more effectively diagnose and remediate mathematics knowledge and skills and, if so, 2) identify the one or two most effective and feasible use cases for further study in a more rigorous Phase II evaluation.

Participants: Participating institutions were identified in November 2017 (Table 1). From December 2017 to January 2018 a team of researchers at the Center for Innovation in Learning and Student Success (CILSS) at the University of Maryland University College (now University of Maryland Global Campus) worked with each institutional team to refine the teams' hypotheses, create strong experimental designs with both treatment and control groups, and ensure that the comparison groups would be as similar as possible.

Table 1. Participating institutions.

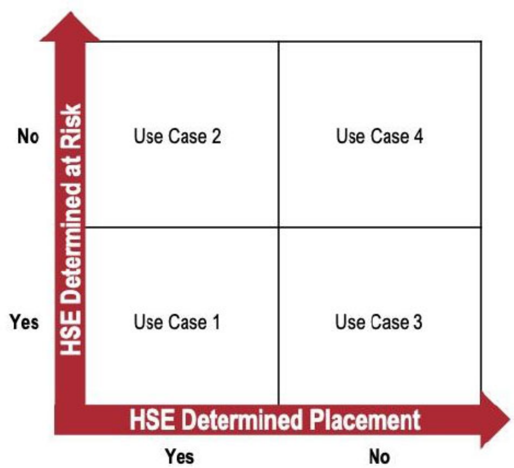
				Pilot				
Institution	**Type**	**Tot. UG Enroll.**	**Ave. # at-risk students/yr**	**Use Case #**	**ALT used**	**HSE used**	**# treatment**	**# control**
Baltimore City Community College (BCCC)	2-year	4,133	300	1	ALEKS	ACCUPLACER	106	106
Bowie State University	4-year	4,711	1,180	3	EdReady	ACCUPLACER	431	455
Carroll Community College	2-year	3,362	300	1	ALEKS	ACCUPLACER	183	213
Chesapeake Community College	2-year	2,189	200	1	ALEKS	ACCUPLACER	148	136
Community College of Baltimore County (CCBC)	2-year	29,115	300	5	ALEKS	ACCUPLACER	1708	1629
Coppin State University	4-year	2,507	500	4	ALEKS	ACCUPLACER	114	235

Institution	Type	Tot. UG Enroll.	Ave. # at-risk students/yr	Pilot Use Case #	ALT used	HSE used	# treatment	# control
Frostburg State University	4-year	4,884	300	5	ALEKS	Institutional	175	175
Howard Community College	2-year	14,220	600	1	ALEKS	ACCUPLACER	435	562
Montgomery College	2-year	22,875	900	2	ALEKS	ACCUPLACER	621	534
University of Baltimore (UB)	4-year	3,222	120	5	EdReady	Institutional	51	8
University of Maryland University College (UMUC)	4-year	44,210	3400	5	ALEKS	ACCUPLACER	141	87
Wor-Wic Community College	2-year	4,109	600	5	ALEKS	ACCUPLACER	242	346
TOTALS		**139,537**	**5,300**				**4355**	**4486**

Procedures: Prior to this project, the participating institutions varied in the way they historically screened students to identify those in need of mathematics remediation. Some required *all* entering students to take a high-stakes exam (HSE). Others first screened students using multiple measures (MM) of mathematics proficiency (including SAT scores, high school GPA, and/or grades on math courses in high school) and required those deemed at risk to take an HSE to determine placement.

While we left the design of the adaptive learning tool (ALT) placement process largely up to the institutions based on their readiness to deviate either significantly or moderately from their current math placement approach, we were happy to have a variety of use cases represented for testing in the pilot. We had two scenarios in which an HSE determined which students were at risk and needed to remediate mathematics deficiencies (Use Cases #1 & 3) and three that used other means to determine at-risk students (Use Cases #2 & 4). We were also pleased to have two scenarios in which an HSE determined placement (Use Cases #1 & 2) and three in which an HSE did *not* determine placement (Use Cases #3 & 4). These different scenarios are graphically illustrated in Figure 1, below.

Figure 1. How each use case employed the HSE.



Data Collection and Analyses: Data collection began in October 2018 and continued through March 2019. To the extent possible, the data collected from each institution included the following for both control and treatment groups:

- Demographic and other data on the students (SAT/ACT, gender, and the like);

● Grades and assessment scores from mathematics placement tests;
● Grades and assessment scores from subsequent mathematics classes taken;
● System data from the adaptive learning tool (either ALEKS PPL or NROC's EdReady).

As anticipated, we found that motivating students to engage with the tools was an issue. Among the 4355 students in treatment groups who were given access to ALT, only 55.7% actually ever logged in to the tools. To avoid the statistical effects of dropout and obtain the average treatment effect on those who actually participated, we conducted intention-to-treat (ITT the average difference between treatment and control) and treatment-on-the-treated analyses (TOT the average treatment effect on compliers –or ITT divided by the percentage of folks who ever logged into ALT). Those analyses are reported below.

Results: Figures 3 to 6 provide comparison data for each use case between treatment and control groups with respect to the numbers of students who placed into a credit-bearing course; placed and enrolled in a credit-bearing course; and placed, enrolled, and completed that credit-bearing course with the grade of C or higher. Analyses include numbers of students (in bars), percentages of students with asterisks to indicate whether differences are statistically significant (just above bars), as well as intent-to-treat (ITT) and treatment-on-the-treatment (TOT) analyses (shown above student percentages).

Figure 3. Use Case #1: HSE->ALT->HSE (BCCC, Carroll, Chesapeake, and Howard)

- CTL n=1017, TRT n=875
- All entering students took the HSE.
- At-risk students randomly assigned to TRT or CTL.
- All students were encouraged to study based on the results of the initial HSE, then re-test using the same HSE for fall placement.

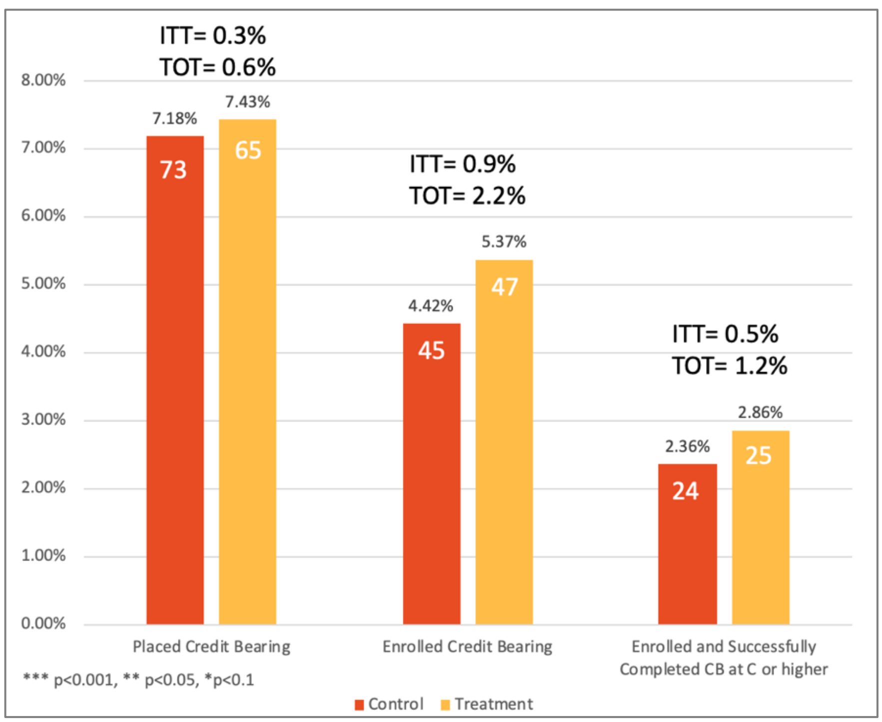


Figure 4. Use Case #2: MM->ALT->HSE (Montgomery College):

- CTL n=534, TRT n=621
- Students identified at risk through multiple measures (MM) then randomly assigned to treatment or control.
- Students encouraged to prepare for the HSE, which they took just prior to the start of fall classes.
- Students were not permitted to retake the HSE.

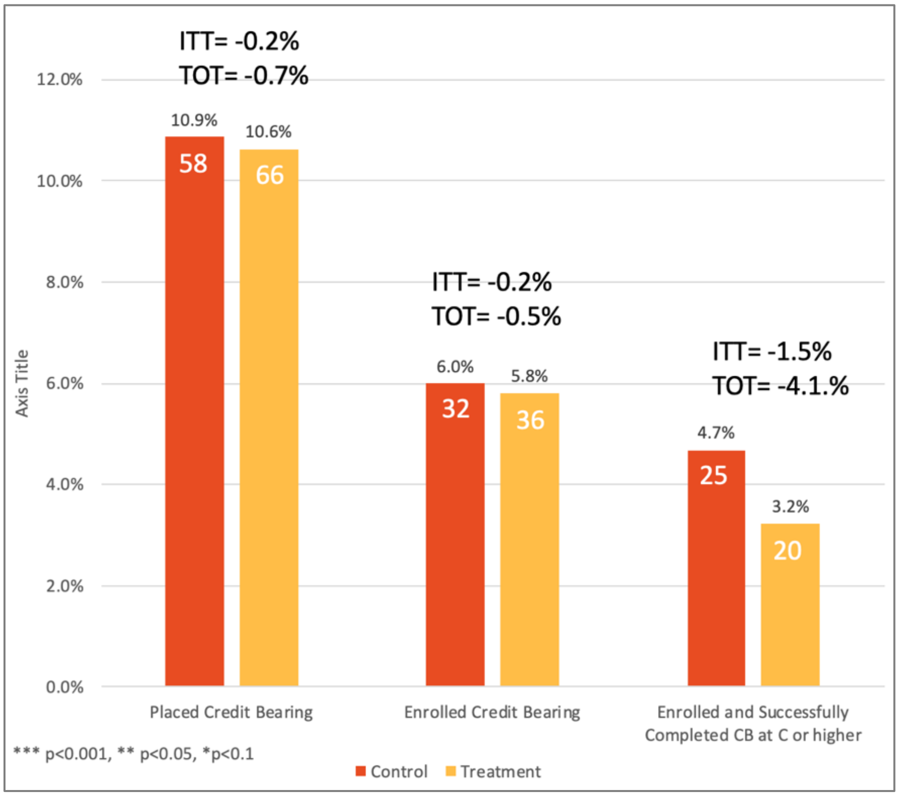


Figure 5. Use Case #3: HSE->ALT (Bowie):

- CTL n=455, TRT n=431
- Students identified as at-risk using HSE then randomly assigned to treatment or control and encouraged to study.
- Students who achieved sufficiently high scores on the ALT diagnostics placed into college-level math.
- Control students retook the HSE for placement.
- Then added 78 CTL and 103 TRT students through MM evaluation.

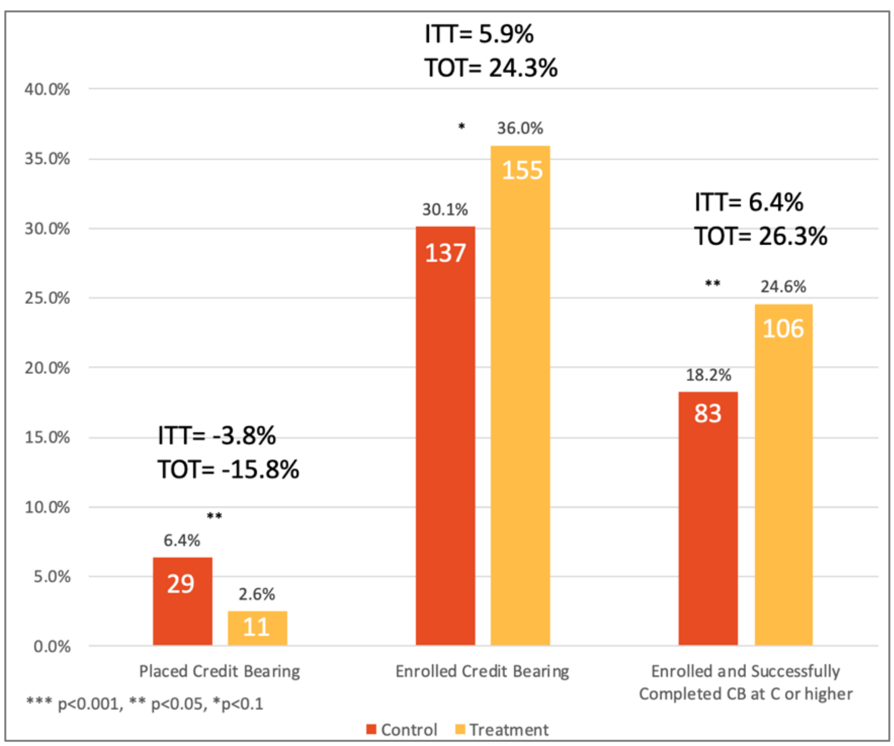
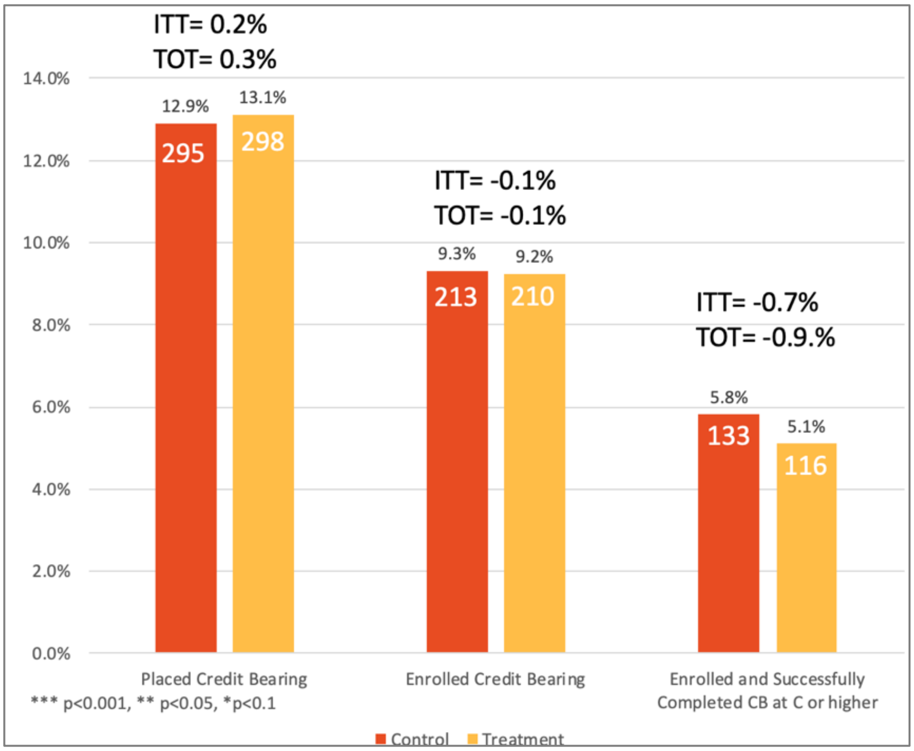


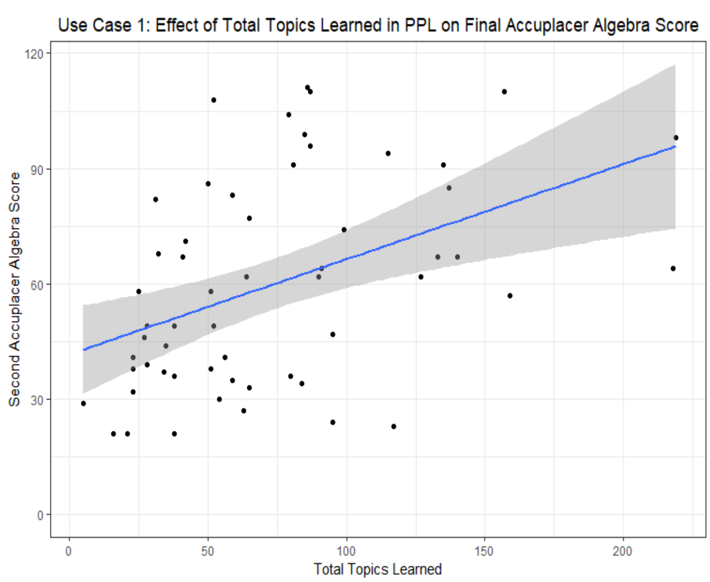
Figure 6. Use Case #4: ALT only (CCBC, Frostburg, UB, UMUC, and Wor-Wic):

- CTL n=2288, TRT n=2273
- All entering students were randomly assigned to treatment or control.
- Treatment students who achieved sufficiently high scores on the ALT diagnostics placed into college-level math.
- Control students took an HSE to determine placement.



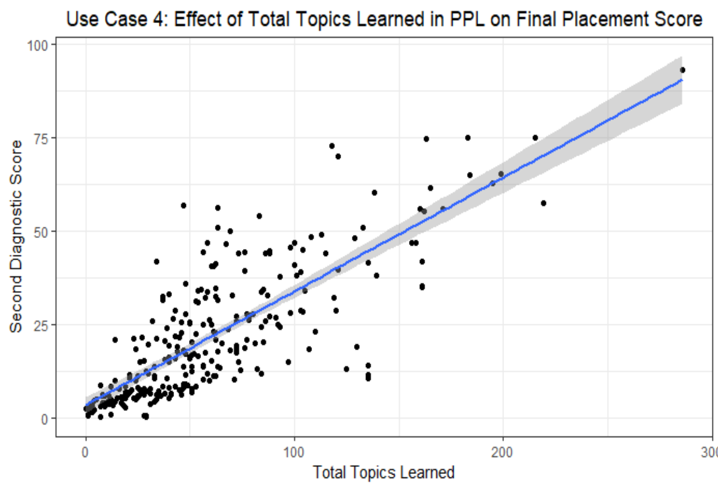
Only Use Case #3 saw statistically significant differences between treatment and control groups, but with negative results for the treatment's impact on students placing in a credit bearing math class. ALT did have a statistically significant positive impact in Use Case #3 on whether students enrolled and whether they also completed that course with a C or higher.

Figure 7. Use Case #1: Effect of total topics learned on final ACCUPLACER score (*r* = 0.247, *p* = 0.001)



In Use Case #1, we found a positive relationship between the total topics learned and the score students achieved on their second Accuplacer Algebra placement attempt (see Figure 7). This suggests that students who learned more topics within ALEKS were able to score higher on their final Accuplacer placement, which would have helped them to bypass developmental math courses by placing directly into credit bearing math. For Use Case #4, there was also a positive relationship between the total topics learned and the score students achieved on their final PPL placement (see Figure 8).

Figure 8. Use Case #4: Effect of total topics learned on final ALT diagnostic score ($r = 0.304$, $p < 0.000$)



Additionally, Use Case #4 was the only use case in which we saw time spent studying in ALT positively impacting both placement and success in the subsequent math course for CCBC, Wor-Wic, and Frostburg's treatment students:

- CCBC: The total number of topics studied in ALT positively impacted subsequent math course grade. Time spent studying was also positively correlated to the diagnostic score gain.
- Wor-Wic: Time spent studying in ALT did not have a statistically significant effect subsequent on the math course grade, but it was positively correlated to the diagnostic score gain.
- Frostburg: Time spent studying in ALT had a statistically significant positive impact on the second diagnostic score as well as the diagnostic score gain.

Discussion: While our findings are generally not supportive of most of our initial hypotheses (see Table 3), as we look across the use cases and reflect on our experiences so far, we have learned a number of important lessons that will guide our work moving forward. Future work needs to…

1. Control for which population is sampled: Allowing variation of use cases created a situation in which the institutions were sampling from different populations. Future iterations of the project will need to standardize on either all incoming students or just those "at risk."
2. Focus on the process rather than the tools: Future studies will need to make clearer to participating institutions that the focus is on their process (proctored/non-proctored, use of nudges to engage treatment students, etc.), not the tools. There are still many questions around proctoring vs. non-proctoring and the extent to which the adaptive tools can be "trusted" over ACCUPLACER. This is something we will need to explore further in the future.

3. Motivate students to engage: Student engagement with the tools was clearly an issue in this study. Unfortunately, early on there was a misunderstanding among some of the institutions about whether they could make use of the “nudging” functions available in the adaptive learning tools. That will be corrected in subsequent iterations of this project. Some of the participating institutions do not have a testing center and/or have very few staff available to monitor student progress in the adaptive tools and manage the process.

4. Ensure fidelity of implementation. As we often see in these kinds of projects, institutions implement research designs with varying fidelity. In the future, we need to be sure we provide the support/follow-up and resources those institutions need in order to stick with the plan.

Table 3. Summary findings for research questions across use cases.

PLACEMENT: Did the ACCUPLACER retest scores of students who used the adaptive learning tools allow them to forego developmental classes at greater rates than the ACCUPLACER retest scores of students who did not use the adaptive learning tools?	No
ENROLLMENT: Do the math course enrollment rates of students who use the adaptive learning tools differ from the math course enrollment rates of students who do not use the adaptive learning tools?	No
COMPLETION: Did the credit-bearing/college-level math course completion rates of students who used the adaptive learning tools differ from the credit-bearing/college-level math course completion rates of students who did not use the adaptive learning tools?	No
LEARNING: Was there a relationship between time spent studying in the adaptive learning tools and student achievement on ALT or HSE diagnostics?	Mixed

There were also several indirect benefits from this project, including:

1. We negotiated a statewide, discounted pricing agreement with McGraw-Hill for ALEKS PPL that makes ongoing use of that tool more sustainable and will likely attract other institutions that are not currently in the project.

2. We engaged institutions in an ROI discussion when we discovered that the difference in cost for ALT compared to HSEs was going to be a challenge for sustainability. To address this concern a toolkit was developed that describes how an institution might consider the costs and benefits of this particular intervention in their specific institutional context to determine ROI.

3. We demonstrated feasibility in this first round of implementations that will allow the institutions to “ease into” the change incrementally, making us better poised for a more controlled and rigorous Phase II project.