2013

Open Academic Analytics Initiative

Final Progress Report

This is the Final Progress Report for the Open Academic Analytics Initiative (OAAI), supported by the EDUCAUSE Next Generation Learning Challenges program.

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Table of Contents

Introduction

As of its ending date of January 21, 2013, the Open Academic Analytics Initiative (OAAI) has successfully achieved all of its major project outcomes including:

- developed and deployed an open-source academic early alert system
- released, under an open-license, our OAAI Predictive Model
- published research on "portability[1]" of predictive models from one academic context to another
- published research on the impact of different intervention strategies on student performance
- disseminated outcomes and research findings to supported adoption of analytics at scale

In addition to these achievements, OAAI was selected as a ***2013 Computerworld Honors Laureate*** in the category of Emerging Technology as well as a recipient of the ***2013 Campus Technology Innovators Award***[2] of which only nine were selected from 235 applications this year.

The following *Final Progress Report* will provide details on our major activities and accomplishments, our researching findings and impact on student performance (course completion, content mastery, and persistence), challenges and lessons learned as well as future plans.

Summary of Activities and Accomplishments

Since beginning our project in May 2011, we have successfully completed the following major activities:

Development Activities: *OAAI Academic Early Alert System [Outcomes 1, 5]*

- ***OAAI Predictive Model*** [*Milestones 2-d, 5-b*] – Produced an OAAI Predictive Model that can predict which students are likely to not succeed in a specific course. This model was developed by applying data mining techniques to a large set of student demographic and aptitude data (e.g. age, SAT scores, etc.) as well as Learning Management System (LMS) event log and gradebook data (e.g. number of course site visits, assignment submissions, etc.) from two full semesters of courses at Marist College.
- ***Pentaho-based ETL-based Data Processing System*** [*Milestones 1-a, 1-b*] – Developed a "Student Effort Data" ETL-based[3] process, using the Pentaho open-source Business Intelligence (BI) suite, for extracting event log and gradebook data from the open-source Sakai Collaboration and Learning Environment (CLE) which was the LMS used in the project. Once extracted, these processes also "clean" or prepare the data in order to standardize its format and coding and then the prepared data is loaded for scoring by the predictive model.
- ***Intervention Strategies*** [*Milestone 3-c*] – Developed, as part of our pilots, two intervention strategies, "awareness messaging" and an Online Academic Support Environment (OASE), which were used by instructors to improve the academic performance of students who had been identified as being "at risk" to not successfully complete the course. In our "awareness messaging" intervention, students who have been identified by our predictive model as being "at risk" receive a

[1] Portability refers the ability to effectively deploy a predictive model in an academic context that is different from where it was originally developed.
[2] The Campus Technology award should remain confidential until June 2013.
[3] ETL stands for Extract, Transform and Load

standardized message from their instructor making them aware of the concern and suggesting how they might improve (e.g., meet with a tutor, take more practice exams, etc.). With the OASE intervention, students receive a similar message but are invited to join an online support community that has been designed to aid academic success. The OASE leverages Sakai Project Sites to provide students with resources including Open Educational Resources (OER) content for remediation and study skill development, facilitation by a professional academic support specialist, and the availability of a student mentor who serves as a peer coach.

Deployment Activities: *Course Pilots [Outcome 3, 4]*

- ***Course Pilots*** [*Milestones 1-d, 2-c, 2-d, 3-b, 3-d*] – Deployed the OAAI Academic Early Alert System across four institutions (two community colleges and two Historically Black College/Universities (HBCUs)) in a total of 65 courses which included 24 instructors and over 2280 students. In addition, we collected data from 26 "control group" courses which included over 880 students.
- ***Data Extractions*** [*Milestones 1-b, 2-c, 3-d*] – Student Demographic and Aptitude Data was extracted from each partner institution's Student Information System (SIS) at the start of both the spring 2012 and fall 2013 semesters. LMS and gradebook data was then extracted three times during both semesters and, along with the SIS data set, used by the OAAI Academic Early Alert System to produce Academic Alert Reports or AARs.
- ***Academic Alert Reports*** [*Milestones 2-c, 3-d*] – These reports, which identified specific students in each course who were at risk to not complete the course successfully, were posted to instructors who then decided if an intervention should be deployed. To assist with this decision, the AARs also included a "confidence rating" (e.g. high, medium or low) indicating the probability that the prediction was correct.

Research Activities: *Portability & Intervention Effectiveness [Outcomes 2, 3, 4]*

- ***Portability Research*** [*Milestones 2-a, 2-b, 2-e*] – Conducted research to analyze the "portability" of the OAAI Predictive Model by first comparing it to the model developed by Dr. John Campbell at Purdue University during his original dissertation work and then assessing the models effectiveness when deployed at our partner institutions (two community colleges and two HBCUs).
- ***Intervention Effectiveness*** [*Milestones 3-b, 3-c, 3-d*] – At the end of both the spring 2012 and fall 2012 semesters we collected final course grade data for all of the students involved in our course pilots, including both treatment and control groups. Analysis was performed to determine if the intervention strategies impacted course completion, content mastery and semester-to-semester persistence rates, looking particularly at the performance of "low income" students.
- ***Student Survey*** [*Milestone 3-d*] – A survey was administered to students at the end of each semester to collect data related to their attitude towards the use of our early alert system and related intervention strategies. The survey also looked at how engaged the students were with their institution using a sub-set of questions from the National Survey of Student Engagement (NSSE).

Dissemination Activities: *Supporting Adoption at Scale [Outcome 5]*

- ***Release OAAI Predictive Model*** [*Milestones 2-d, 5-b*] – A final refined OAAI Predictive Model has now been released under an open license in the standards-based Predictive Model Markup Language (PMML) to allow use by other institutions and researchers.

- ***Release ETL-based Processes and Project Documentation*** [*Milestones 1-e, 5-c*] – We have released, under Creative Commons licenses, all of the technical details related to the ETL-based processes that were developed as well as all product documentation (e.g. Instructor Guides, Online Academic Support Environment Design Framework, Data Security Protocols, etc.) to the Sakai Community Wiki[4].
- ***Publish Research Findings*** [*Milestones 5-c, 5-d*] – Research findings related to portability and our initial analysis of our spring 2012 course pilots have been published in the peer-reviewed proceedings for the 2012 and 2013 International Learning Analytics and Knowledge (LAK) conferences, respectively (see references below). Our final findings are in the process of being submitted for publication in the inaugural issue of the *Journal of Learning Analytics* published by the Society for Learning Analytics Research (SoLAR). We are also in the process of completing a Seeking Evidence of Impact (SEI) Case Study on our work for the EDUCAUSE Learning Initiative.
  - Lauría E., Baron J., Devireddy M., Sundararaju V., Jayaprakash S. (2012), Mining Academic Data to Improve College Student Retention: An Open Source Perspective. In Proceedings of the 2nd International Conference on Learning Analytics and Knowledge (LAK '12), Simon Buckingham Shum, Dragan Gasevic, and Rebecca Ferguson (Eds.). ACM, New York, NY, USA, 139-142
  - Lauría E., Moody E., Jayaprakash S., Jonnalagadda N., Baron J. (2012), Open Academic Analytics Initiative: Initial Research Findings, Proceedings of the 3rd International Conference on Learning Analytics and Knowledge LAK '13, April 08 - 12 2013, Leuven, Belgium
- ***Conference Presentations*** [*Milestones 5-c, 5-d*] – Our project and related findings have been presented at a range of national and international conferences including: 2012 International Jasig-Sakai Conference, 2012 EDUCAUSE conference, 2012 and 2013 International Learning Analytics and Knowledge (LAK) conferences, North East Regional Learning Analytics Symposium (NERLA) and NERCOMP Senior Leadership Forum. We will be presenting at the 2013 Apereo Foundation (organization resulting from the merger of Sakai and Jasig) conference and have submitted a proposal for the 2013 EDUCAUSE conference.

Project Findings and Impact

Our research findings related to both the "portability" of predictive models and the impact of our intervention strategies on student performance (i.e. course completion, content mastery and semester-to-semester persistence)[5]. Our research efforts were associated with three of our five major project outcomes (specifically Outcomes #2, #3, and #4) and were among our most significant accomplishments. We have published two papers in peer-review journals to date related to our initial findings (see above) and are in the process of submitting a third paper, to the Journal of Learning Analytics, that will discuss our final project findings.

The following **summarizes our key findings** which are discussed in more detail in the following sections:

- Predictive models can be "ported" from one academic context to another and retain most of their predictive power. The OAAI Predictive Model remained in the 60-85% accuracy range (depending on institution) when deployed in our course pilots.

[4] See https://confluence.sakaiproject.org/display/NGLCOAA

[5] As noted in our original grant proposal, researching "deeper learning" was beyond the scope of our project due to time and resource constraints and thus was not part of our stated project outcomes.

- Overall, our interventions had a positive and statistically significant (*p* = .013) impact on average course grades. This positive trend was also found among "low income" students although just under the statistically significance level (*p* = .054).
- Overall, our interventions had a positive and statistically significant (*p* = .001) impact on content mastery. This positive trend, which was also statistically significant (*p* = .023), was also found when we considered only "low income" students.
- We found that course completion rates were higher among our control group (91%) then our treatment groups (85%) which were also found to be a statistically significant trend. In analyzing this finding in more detail, we determined that students in our treatment groups may be withdrawing from courses earlier than those in our controls which may explain this apparent reversal in the expected outcome.
- We also found that there was no statistically significant difference in semester-to-semester persistence rates between our controls and treatment groups. We believe this may be the result of the limited scope of our pilots and the fact that we were impacting, at most, on only one of several courses that students were taking during the spring semester.

These findings, particularly those related to the impact of our intervention strategies, directly relate to NGLC's overall goal of dramatically improving student outcomes in college completion and demonstrate the positive impact OAAI has had on this goal.

Findings Related to Portability of Predictive Models

During the summer of 2011 the analytics research team at Marist College developed a predictive model using the same student demographic (e.g. age), aptitude (e.g. SAT scores), and learning management system usage (e.g. number of course visits) used by Dr. John Campbell at Purdue University in his original dissertation research except our data was from Marist students and based on usage of the Sakai[6] Learning Management System (LMS). Although Marist College and Purdue University differ in obvious ways (e.g., institutional type, size, and instructional approaches) they do share a number of similarities which are particularly pertinent to this study. These include percentage of students receiving federal Pell Grants (Marist 11%, Purdue 14%), percentage Asian/Black/African American/Hispanic students (Marist 11%, Purdue 11%), and ACT composite 25th/75th percentile (Marist 23/27, Purdue 23/29).

Table 1 - Correlations between course grades and CMS

Undergraduate CMS event frequencies		Course Grade: Marist Fall 2010 N=18968	Course Grade: Campbell (2007) N=27276
Sessions Opened	Correlation	0.147	(no values reported)
	Significance	0.000(**)	
	N	11195	
Content Viewed	Correlation	0.098	0.112
	Significance	0.000(**)	0.000(**)
	N	7651	19205
Discussions Read	Correlation	0.133	0.068
	Significance	0.000(**)	0.000(**)
	N	1552	7667
Discussions Posted	Correlation	0.233	0.061
	Significance	0.000(**)	0.000(**)
	N	1507	7292
Assign. Submitted	Correlation	0.146	0.163
	Significance	0.000(**)	0.000(**)
	N	3245	4309
Asssmts Submitted	Correlation	0.161	0.238
	Significance	0.000(**)	0.000(**)
	N	1423	4085

(**) Significant at the 0.01 level (2-tailed)
Marist data uses ratios over course mean instead of frequencies

Once the Marist predictive model was developed, we compared the elements of the model that were statistically significant with regards to correlation with student grades (as was done at Purdue) as means to understand to the degree to which the model we developed using Marist student data differed from Purdue's model. In general, we found the same statistically significant elements as Purdue with similar correlation strengths (see Table 1). The OAAI analytics research team published a paper (*Mining Academic Data to Improve College Student Retention: An Open Source Perspective*), related to this initial

[6] Purdue was using WebCT/BlackBoard in their research.

research on “portability” which was presented at the 2012 international Learning Analytics and Knowledge (LAK) conference.

Classification Algorithm	Performance Metrics	Mean	SE
SVN / SMO	Accuracy	85.96%	0.86%
	Recall	81.24%	4.55%
	Specificity	86.31%	1.24%
	Precision	31.81%	2.16%
C5.0 / J48	Accuracy	86.82%	1.14%
	Recall	65.45%	3.85%
	Specificity	88.31%	1.48%
	Precision	31.34%	2.52%
Logistic Reg.	Accuracy	86.07%	0.92%
	Recall	80.26%	5.18%
	Specificity	86.53%	1.35%
	Precision	33.01%	3.44%

Table 2 - Prediction analysis using Marist test data

After the phase one research efforts, time was spent enhancing the initial predictive model through machine learning techniques and the introduction of additional data elements, specifically data from the Sakai Gradebook (e.g. quizzes, homework, etc).[7] The enhanced predictive model was then evaluated using a Marist test data set which had been excluded during the original development of the model. Table 2 provides a summary of the outcomes from this evaluation (a total of ten trials were run but the table only includes the means from these tests).

This model was then deployed as part of our course pilots during the spring and fall 2012 semesters with two community colleges and a HBCU which represent vastly different educational contexts as compared to Marist. For example, Savannah State University has a 94% Black non-Hispanic student population with 67% of receiving Pell Grants, College of the Redwoods’ student population has 22% minorities and 60% are receiving Pell Grants and Cerritos College’s student body is 41% Hispanic and 45% of the students are receiving Pell Grants.

	College	AAR run	# Students	Accuracy	FP Rate	Precision	Recall
Spring 2012	Savannah	AAR1	504	67.26%	35.36%	61.48%	70.54%
		AAR2	504	74.40%	32.50%	67.15%	83.04%
		AAR3	504	79.37%	18.21%	77.03%	76.34%
	Cerritos	AAR1	502	61.95%	43.69%	47.41%	72.32%
		AAR2	601	71.88%	27.49%	59.62%	70.78%
		AAR3	649	75.19%	25.12%	62.50%	75.76%
	Redwoods	AAR1	195	67.69%	40.48%	52.78%	82.61%
		AAR2	195	78.97%	13.49%	72.58%	65.22%
		AAR3	195	77.95%	14.29%	70.97%	63.77%

	College	AAR run	# Students	Accuracy	FP Rate	Precision	Recall
Fall 2012	Savannah	AAR1	425	68.47%	38.34%	58.19%	78.49%
		AAR2	425	72.59%	30.04%	65.17%	76.16%
		AAR3	425	73.41%	26.88%	65.13%	73.84%
	Cerritos	AAR1	502	65.38%	32.35%	49.49%	61.01%
		AAR2	601	70.75%	27.78%	55.96%	67.92%
		AAR3	649	73.98%	24.51%	60.11%	71.07%
	Redwoods	AAR1	182	83.63%	16.52%	71.21%	83.93%
		AAR2	182	83.82%	16.52%	72.06%	84.48%
		AAR3	182	85.63%	13.04%	76.56%	83.05%
	NCAT	AAR1	719	64.12%	31.25%	26.53%	45.45%
		AAR2	719	71.07%	24.83%	35.29%	54.55%
		AAR3	719	75.10%	20.14%	40.82%	55.94%

Table 3 - Prediction analysis on spring and fall pilot data

At the conclusion of the project an analysis was completed to determine how well the model performed when deployed in these different academic contexts. This evaluation included assessing the model’s performance at three points during the semester (25%, 50% and 75% of the semester completed), which correspond to when Academic Alert Reports (AAR 1, AAR 2 and AAR 3 respectively) were provided to instructors, as means to understand how the model’s performance changed as more LMS and gradebook data was available. Table 3 provides a summary of the results of this evaluation. Looking at the accuracy of the model (percentage of students that were correctly identified), just as one indicator, it is clear that the results from the predictive analysis were considerably higher than sheer randomness. For example, when one compares the accuracy of AAR #3, which ranged from 75% to 79%, to the accuracy of the model when tested with Marist data (which was historical and thus represented 100% of the semester completed), which was 86-87%, we find only a 6-10% difference. Given that we expected a much larger difference between how the model performed when tested with Marist data and when deployed at community colleges and HBCUs, this was an encouraging finding.

[7] In recent years Course Signals has also added gradebook data elements to their predictive model.

Findings Related to Intervention Effectiveness

Over the spring and fall 2012 semesters we conducted a series of institutional pilots which, in general, included introductory-level courses in which the same instructor taught three sections of the same course. The three sections of each course were assigned to be part of either a control or one of two treatment groups. For the control group, no interventions were deployed, although data on student performance and predictions from the OAAI early alert system were still collected. The other two sections acted as "treatment groups" and received either the "awareness messaging" or Online Academic Support Environment (OASE) intervention. In total, we had over 1,300 students in our two treatment groups combined and over 700 in our control group[8].

In our "awareness messaging" intervention, students who have been identified by our predictive model as being "at risk" to not complete their course receive a standardized message from their instructor making them aware of the concern and suggesting how they might improve (e.g., meet with a tutor, take more practice exams, etc.). With the OASE intervention, students receive a similar message but are invited to join an online support community that has been designed to aid academic success. The OASE leverages Sakai Project Sites to provide students with resources including Open Educational Resources (OER) content for remediation and study skill development, facilitation by a professional academic support specialist, and the availability of a student mentor who serves as a peer coach.

Finding #1: Impact on Average Course Grades

Our research shows that our interventions had a statistically significant impact on overall course grades. To determine this we conducted a one-way ANOVA analysis comparing the two treatment groups and the control groups (including all students in the assigned sections regardless of their performance). This also included students in the treatment groups who did not actually receive an intervention. Table 4 shows the results of this analysis which had a significance level of $p = .013$.

	Awareness	OASE	Control
Mean	78.51	78.27	76.56
n	642	659	719

$F(2, 2017) = 4.360 = .013^*$

Table 4 - ANOVA analysis of average course grades

It is important to note that we did not find any significant differences between the two treatment groups (awareness and OASE) which appear to have nearly identical mean course grades. This seems to indicate that although both intervention strategies had an impact on student performance, neither intervention was more effective than the other. Our theory as to why this has occurred is that in both interventions students receive similar messages from their instructor expressing concern over their performance, it is only the action the student is encouraged to take (e.g. see a tutor vs. join the OASE) that differs. This leads us to conclude that it is the messaging to the student that is the driving factor in the improvement in the student's performance rather than the specific actions that are recommended. It is also relevant to note that few students appeared to have used the OASE to any large extent and thus we would recommend additional research be conducted into how to better engage students in such a support resource as this could lead to increased impact on student performance.

We also conducted a more refined analysis looking at a sub-set of the overall student population in our study as means to more narrowly examine the impact of the interventions. To do this, we compared students in our treatment groups who received at least one intervention to students in our controls who we believed would have received interventions if they had been in a treatment group. We identified this sub-set of control group students by selecting only those students who our predictive model had

[8] This represents a sub-set of the total student population involved in our course pilots as data was not used if questions existed regarding its validity.

identified, with a "medium" or "high" confidence level, as being at risk to not complete their course (we did not include "low" or "no" confidence level students). We believe this is a valid method of identifying this sub-set of control group students as we have been able to determine, from our treatment group data, that those students who were identified at a medium or high confidence level did, in the vast majority of times, receive an intervention from their instructor.

Using this sub-set of our overall student population, our refined one-way ANOVA analysis (see Table 5) shows a greater statistical significance level (p = .001 rather than .013) which further confirms our conclusion that our intervention strategies had a real and positive impact on student performance. In addition, we see that the differences in average course grades between the two treatment groups (awareness and OASE) only different by .01 percentage points. This also appears to support our theory that the messaging aspect of our interventions is what resulted in this positive effect.

	Awareness	OASE	Control
Mean	70.99	70.98	66.66
n	287	261	169

F (2, 714) = 7.076 = .001*

Table 5 - Refined ANOVA analysis of average course grades

Finally, when we looked at only "low income" students (those receiving Pell Grants) our ANOVA analysis showed (see Table 6) a positive trend with regards to the interventions impacting on their average course grades but it was just under the statistical significance level (p = .054). Interestingly, when we conducted a more refined analysis (see Table 7) looking at just those students who were or we believe would have been intervened we found a high significance level (p = .004). This leads us to believe that with a larger sample size that we would likely find a statistically significant result from the more general analysis.

	Awareness	OASE	Control
Mean	77.44	76.57	75.30
n	435	420	465

F (2, 1317) = 2.931 = .054. N.S. This is not significant

Table 6 - ANOVA analysis of average course grade among low income students

	Awareness	OASE	Control
Mean	70.10	70.08	65.45
n	200	187	112

F (2, 496) = 5.683 = .004*

Table 7 - Refined ANOVA analysis of average course grades among low income students

Finding #2: Impact on Content Mastery

Our research has also shown a statistically significant impact on content mastery (students who received a course grade of a C or higher). This was determined through a Chi-Square analysis comparing all students in our treatment groups (awareness and OASE combined) with students in our control groups. Table 8 shows the results of this analysis which indicates a high level of significance (p = .001) in this finding. We also looked at the impact of our interventions on content mastery among "low income" students which was also found to be statistically significant (p = .023) although not as strong as the general student population.

		Group	
		Control	Treatment
Content Mastery	Yes	502	997
	No	227	320

Chi-Square (1) = 11.211, p = .001;*

Table 8 - Chi-Square analysis of content mastery

As with the overall course grades, we also conducted a more refined analysis looking at just those students in our treatment groups who were intervened and those in our controls who we believe would have been intervened. This showed a similar trend as the overall analysis but it fell slightly below the significance level (p = .077). In analyzing our spring and fall data separately, we discovered that the trend in the spring semester was significant (p = .021) but the trend in the fall was not (p = .753). In further reviewing our data from the fall we discovered that instructors, for reasons we are unsure of, had a strong tendency towards only deploying interventions to those students who's predictions were at the "medium" or "high" confidence levels (whereas in the spring they had tended to also deploy to those

		Group	
		Control	Treatment
Content Mastery	Yes	106	69
	No	34	20

Chi-Square (1) = 0.099, p = .753 N.S

Table 9 - Refined chi-square analysis of content mastery (fall 2012)

with "low" rating). From our analysis we have also determined that students in this category do not respond to the interventions as much as those with "low" confidence level ratings. Thus, an explanation for why the overall refined analysis is not significant may be the tendency of instructors in the fall to not deploy intervention in the same way as the spring and that this difference lowered the overall significance.

Finding #3: Impact on Course Completion

In analyzing course completion rates we found what initially appears to be a reversal in expected or desired trends. When considering course completion rates of our overall student population we found that our control group had higher completion rates (91%) than our combined treatment groups (85%), which did represent a statistically significant trend (see Table 10). When we conducted this same analysis with only our "low income" students we found a similar trend that was also significant (p = .030).

		Group	
		Control	Treatment
Course Completion	Yes	729	1317
	No	73	230

Chi-Square (1) = 15.626, p = .000*

Table 10 - Chi-square analysis of course completion rates

To better understand the cause of this unexpected trend, we analyzed withdrawal rates after the first Academic Alert Report was distributed to gain insights into how initial interventions may be impacting students' decisions to withdraw from the course before receiving significant penalties. We found that students in our combined treatment groups were in fact withdrawing more frequently (17%) versus those in our control groups (9%) which was also a statistically significant trend. This trend is also consistent with findings at Purdue University in courses using their Course Signals analytics solution. Based on this, we believe that it is likely that we are seeing lower completion rates among those students who received interventions because these students were more likely to drop their course after receiving an intervention. Although ideally we would like to see students successfully completing courses, having them withdraw early in the course and avoid financial and other penalties is a positive outcome. This appears to be an area that would benefit from additional research.

		Group	
		Control	Treatment
Withdrawal	Yes	76	203
	No	729	1012

Chi-Square (1) = 21.479 p= .000*

Table 11 - Chi-square analysis of withdrawal rates among all students

Finding #4: Impact on Semester-to-Semester Persistence

Our analysis regarding semester-to-semester persistence rates resulted in inconclusive findings that would benefit from additional research. In looking at our overall student population, we found that persistence rates were slightly higher for our controls (74%) then for our combined treatment groups (70%). Unfortunately, our findings in this area were not statistically significant (see Table 12) and thus we cannot draw any definitive conclusions. When we considered only "low income" students the differences in persistence rates between the control (75%) and treatment (73%) became smaller but again were not statistically significant (p = .523).

		Group	
		Control	Treatment
Persistence	Yes	238	744
	No	82	315

Chi-Square (1) = 2.035, p = .154; N.S

Table 12 - Chi-Square analysis of persistence rates among all students

One explanation for this outcome may relate to the limited scope of our deployment of learning analytics at our partner institutions as in the vast majority of cases students were only enrolled in one course in which OAAI was used. For students taking three or four courses, this would mean that we only affected a small portion of their overall academic performance at their institution. Thus, although we may have had a positive impact on the outcome in one of their courses this may have not been enough to convince them to continue with their education and enroll in the following semester.

Project Challenges and Lessons Learned

Although we were able to achieve our five major project outcomes, we did encounter challenges over the duration of our project and learned many lessons, all of which we will apply to future projects.

Challenge #1: Discontinuation of Institutional Partners

Early on in the project we had two of our original institutional partners, American Public University System (APUS) and Howard University discontinue due to local internal issues that limited their ability to participate. To address this, we quickly found another institution, North Carolina A&T, who had originally expressed interest in being part of our proposal, and invited them to replace Howard University. We also asked our remaining partners to run additional pilots as means to ensure we had large enough sample sizes. The need to bring onboard North Carolina A&T was a factor in our decision to request a six month no-cost extension. Despite these challenges, we were able to run our pilots successfully and, in most cases, obtain sample sizes that were large enough to conduct valid statistical analysis.

Challenge #2: Initial Delays with Analytics and Technical Work

We encountered several unexpected delays at the start of our project related to the development of our predictive model and some of the technical work needed to deploy it in our pilots. To address this, as part of our no-cost extension request, received permission to shift our course pilots from fall 2011/spring 2012 to spring 2012/fall 2012 to allow us to fully prepare. This shift had the added advantage of allowing us to collect spring-to-fall persistence data which was more useful then fall-to-spring data.

Challenge #3: Student Effort Data API Strategy

After an in-depth technical assessment of our original strategy of developing an Application Programming Interface (API) for Sakai that would extract and prepare the necessary event log and gradebook data, we identified a number of previously unknown challenges. In particular, we realized that because of the range of different ways Sakai can be implemented, trying to develop one API that would work for all Sakai institutions was not realistic. We also realized that building these functions into Sakai would reduce flexibility and make it hard to adapt over time. To address these challenges, we adopted a new technical strategy around using Pentaho's ETL (Extraction, Transformation and Load) capabilities to perform the same basic tasks as the API would have done. This had the advantage of accommodating a wide range of Sakai configurations with minimal technical work while also leveraging the extensive knowledge of Pentaho that we had developed.

Challenge #4: Limited Use of the Online Academic Support Environment

As noted in the Project Findings and Impact section, after our first round of course pilots in spring 2012 we found that only a few students used the OASE and even then only engaged with it on a limited basis. Based on informal feedback from the partner sites, we decided to re-design aspects of the OASE for the fall 2012 pilots to try and increase engagement with the students. For example, we created a very brief survey that we asked them to complete when they first entered the site that was designed to gather initial information on how we might best provide them with support. Although we believe these changes did improve use of OASE, additional research into how to better engage students in such an environment would be recommended.

Lesson Learned #1: Collaboration Benefits and Costs

We believe the project benefited significantly, both directly and indirectly, from collaborating with our project partners. Clearly, we would not have been able to conduct our research efforts without a diverse set of institutional partners who were willing to run course pilots and assist in data collection. More indirectly, we were able to leverage our relationships to help address project challenges. For example, it was a prior relationship between the Information Technology Senior Management Forum and North Carolina A&T which allowed us to bring them on quickly to replace Howard University. These benefits note there was a normal "cost" of time and effort, particularly around communication and coordination, associated with this collaboration which was non-trivial. One lesson learned in this regard was the scheduling of our grant partner meeting which took place in October 2011, several months after the start of the grant. In hindsight, holding this meeting at the start of the grant would have allowed us to build working relationships among the project coordinators early on in our work.

It is also worthwhile noting the important role that the larger NGLC community played with regards to collaboration. From timely responses to our questions to connections we made through events such as the NGLC Wave 1 "convening" and various webinars, the NGLC program and staff was invaluable to our success. We would recommend that similar, if not more, support be provided to future NGLC grant recipients.

Lesson Learned #2: Importance of IRB Approval and Data Security

Early on in the project we dedicated a significant amount of time and effort to ensure that Marist's Institutional Review Board (IRB), Registrar and Office of Institutional Research had all reviewed our research plans and data security protocols and approved them. The value of this work became particularly clear as we began our course pilots at our partner institutions as the fact that we had gained extensive approvals from Marist already made it much easier to gain local approvals from our partners.

Lesson Learned #3: Clarity of Survey Questions

A small subset of the survey questions on our Student Survey, which we had not validated as the others had been, were not clear to students and resulted in answers which we did not feel were accurate. We had to remove this data from our analysis as a result. If we had validated all questions we could have likely avoided this problem.

Scaling Strategies and Future Goals

We have been actively disseminating information on OAAI throughout the project through papers, conference presentations and webinars as part of our efforts to scale adoption of OAAI. As we conclude the grant we are already seeing evidence of our success in this area with the Kaleidoscope project, another NGLC Wave I grant recipient, deciding to adopt components of OAAI as their analytics solution. We are also currently consulting for the South Orange County Community College District (SOCCCD) who are in the planning phases of their own learning analytics project and may opt to utilize OAAI as well. In addition to these specific adoption activities, we have spoken directly with three additional institutions who are considering use of OAAI in the near-term. Finally, we are also planning to develop a customized predictive model for our online Master of Public Administration program at Marist.

Beyond these current scaling activities, we are also assessing the feasibility of launching a formal "open analytics project" under the open-source software Apereo Foundation (www.apereo.org). This project would allow us, and other institutions that chose to get involved, to build on top of our OAAI work and develop a comprehensive open-source learning analytics solution. Such a solution could include: a cloud-based open-source learning analytics engine, a library of open predictive models, open data sets for testing and training, a learning analytics dashboard for Sakai, and open standards for learning analytics. As a first step in assessing the feasibility of such a project, we will be organizing an Open Learning Analytics Summit at the 2013 Apereo conference in San Diego, CA in early June.