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The Predictive Quality of High School Grade Point Average on the Outcomes of Under-prepared Students in a Mathematics Intervention Course for First-year Engineering Students: How Motivation and Effort Correlate to Student Success

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Abstract
Previous research on the impact of a mathematics intervention course on engineering students revealed a strong correlation between students' high school grade point averages (HS GPA), academic conscientiousness and motivation. Further analysis revealed a better than expected graduation rate after this intervention course for students with higher than average HS GPAs, even for students with below average ACT Math scores. The increases in graduation rates were determined to be primarily due to increases in mathematics self-efficacy, while motivation and effort were only tangentially discussed. While these have been considered factors for success in previous studies, the focus of these studies has been primarily on students that are academically prepared for engineering programs (i.e., ACT Math >25). This paper focuses on a mathematics intervention course designed to remediate and increase the math placement level (MPL) of underprepared students in their first semester of engineering. The course utilizes both a lecture session, where engineering concepts in math are covered in a topic based linear approach, and an online browser-based program, where students can self-pace through pure mathematics topics. The course structure allows for tracking of time spent on self-paced tasks online and comparisons with lecture based assignments to aid in the determination of student motivation. Additionally, students retake the university math placement test twice during the semester in order to move ahead in the math curriculum through the remediation process of the course. In a population of underprepared first-year engineering students taking a mathematics intervention course, the objectives of this study are to determine if HS GPAs can predict student effort level (i.e., time-on-task), if that effort leads to superior outcomes (i.e., MPL and knowledge gained), and if course objectives incentivize student effort during course progression. The study covers 2 semesters of the course and includes 209 new direct from high school (NDFHS) students. Additional information regarding the 70 minority students and 35 female students that make up a portion of the 209 test subjects is also discussed. Applications of study outcomes are discussed in terms of targeted enrollment management and student success predictions.

Background – Closing the Postsecondary Attainment Gap
In recent years, there has been an increased push for Ohioans to complete postsecondary training to compete with the national and global market (NCHEMS, 2010; Ohio Higher Ed, 2016). The barriers to success most often discussed in the publications are cost and time. These issues are not the primary factors related to engineering degrees, however, as research has shown. (Alarcon, 2012; Bourne, 2014; Brown 2008; Connor 2007; DeFeyter, 2012; Hazrait-Viari, 2011; Komarraju, 2011; Lent 1984; Lent 1991; Moreira, 2013; Poropat, 2009; Robbins 2004; Wang, 2013). The issues related to increasing engineering degree attainment are created through the broadening of the incoming pool of NDFHS students, a clear majority of which, comes from underprepared students entering programs that are not designed to meet their needs or increase their chance of success.

To better understand if opportunity exists to create support programs for underprepared students, previous studies endeavored to determine the role psychosocial factors play in achievement for some underprepared students (Bourne, 2014). The results of this study showed that motivation and conscientiousness play key roles in student outcomes, and these factors can be predicted using the measures of objective academic performance (MOAPs), HS GPA and ACT math scores. The combination of these MOAPs resulted in the creation of the Academic Performance-Commitment Matrix (APCM), which shows student-types based on a four-quadrant matrix of these MOAPs.

Further study into these findings showed especially beneficial effects on mathematics self-efficacy of the Support Seeker quadrant of the APCM and lead to considerations that this group may benefit most from supportive academic environments and may be recruited more heavily as a part of an enrollment management policy of a university. (Bourne, 2015) Mathematics self-efficacy as an impact on achievement has been long studied and supports these findings. (Ayotola, 2009; Bndura, 1977; Barker, 2010; Burnham, 2011; Cordero 2010; Gore, 2006; Lent, 1996; Pajares, 1995; Vuong, 2010).

Open enrollment institutions, like the one used for this study, allow students of all academic preparedness to enter engineering curriculums once they pass the prerequisite mathematics courses. Many students begin in developmental or college algebra courses where student types have not been extensively studied in the engineering academic environment. Where most research on students of this type has been focused on community college programs designed to limit early drop out, there is a dearth of research conducted on programs designed to not only retain, but aid in the retention and success of these students.

The course at the Wright State University called Preparatory Math for Engineering (EGR1980) has been run since 2008, with the latest iterations being implemented in 2012. Students that place into either developmental math or college algebra are enrolled in the course. Many of these placements, however, are below where the student should be placed based on previously completed coursework. However, these students have scored a 24 or lower on the ACT math test, or have taken the university math placement exam and been placed at this level based on that score.

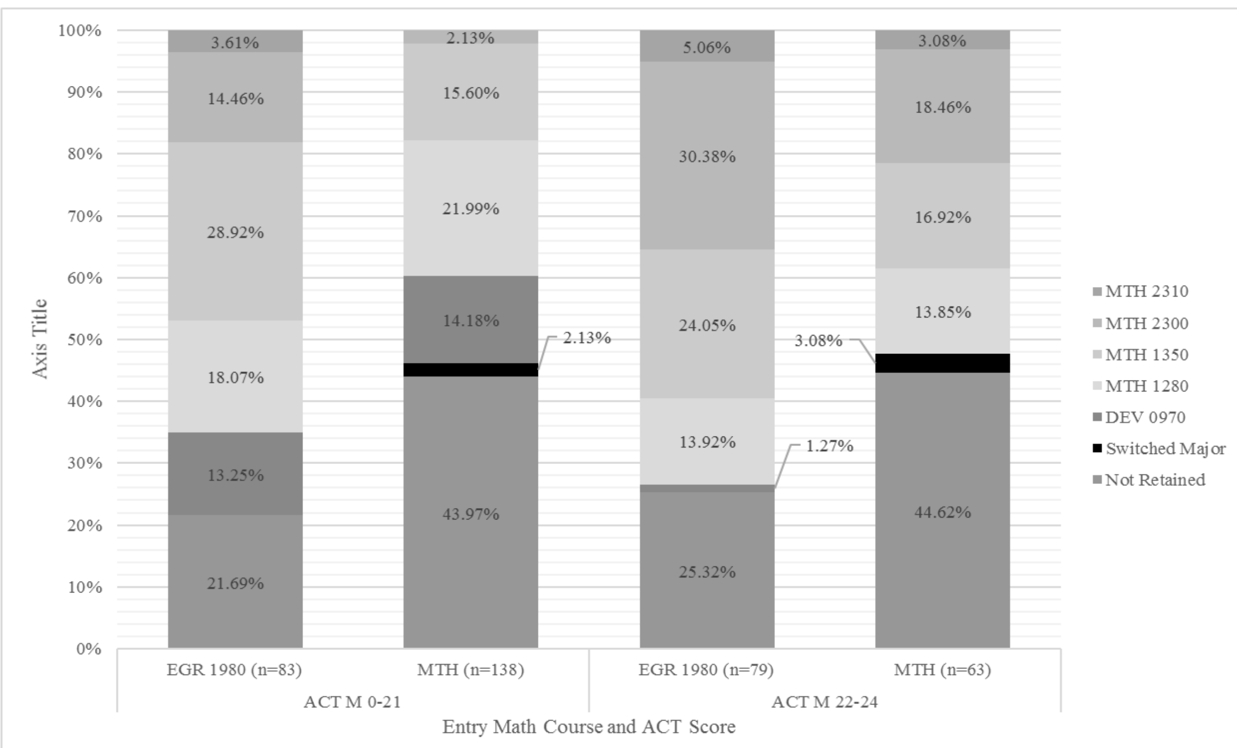

Figure 1. Highest math course enrolled in three semesters after taking an introductory math class or EGR1980 by ACT Math Score

Figure 1 shows the comparison between two available pathways for students seeking to obtain an engineering degree for two ACT math bins. The traditional route includes starting in the math remediation courses Developmental Math (DEV0970) or College Algebra (MTH1280) and upon successively completing them, move to pre-calculus/trigonometry, and then calculus. The math intervention course EGR1980 is the nontraditional route and provides students an opportunity to increase their math placement level (MPL) (sometimes multiple levels) in one semester. Data depicts the percentage of students qualifying for a given math class one year after taking either EGR1980 or DEV 0970/MTH 1280. Students taking the engineering math intervention course were retained in the college of engineering at much higher rates (over 70% versus roughly 56%) and were also farther along in the math curriculum one year later.

This improvement is achieved by providing the students an opportunity to remediate and retake the math placement test in a given semester and by providing math-in-context examples through engineering based lectures. By providing an opportunity for students increase their placement score high enough to move more than one course through the curriculum, they are incentivized to work through and persist through any difficult topics. This may be a superior motivator for some students.

In Fall of 2015 the course was modified again and began using an online math remediation tool called an Assessment of Learning in Knowledge Spaces (ALEKS). This web-based program allows students to log in and pace themselves through mathematics topics in need of improvement. At the beginning of the course, students take an assessment and are shown areas of deficiency in the math curriculum (algebra through pre-calculus). Students then move at their own pace through the online tool along with working as a group in the online activities. The goal of the course is to have the students place into the appropriate mathematics level based on their knowledge from high school and subsequent knowledge obtained in the course.

Given that previous research showed a strong correlation between success in the classroom and incoming HS GPA, (Bourne 2014, Bourne 2015) it is easy to assume that the same correlation holds for the far underprepared student group. This assumption was not strong, however, as students that are far below the calculus standard have multiple curricular hurdles to overcome and HS GPA may not be an important factor effecting the academic outcome. Additionally, there is a research gap with respect to the cause of what behaviors are attributed to having a higher HS GPA as it correlates to academic conscientiousness. While ACT calls this measure “Commitment to College”, it is aligned with a state of mind, rather than an actual activity or action that students take.

Given the structure, academic demographics of the student population, and the relative success of the course, it holds that a study into the impact of HS GPA in this context may yield a greater understanding of the breadth of conscientiousness in effort toward success, and may also provide detail into what that effort looks like.

Study

There are three main objectives of this study:

1- Determine if HS GPAs of underprepared first-year engineering students can predict conscientiousness (effort) in an engineering mathematics intervention course
2- Show that effort in the course leads to superior outcomes of course objectives including improvement in MPL and also greater time in an online self-paced component of the course
3- Discover if the course objectives incentivize student effort as the course progresses.

Objective 1
To determine the correlation between HS GPA and effort, a regression analysis utilized the most likely contributors to students' success in relation to the increase in the MPL scores of the students. Figure 2 shows the outcome of this regression where ACTMath is a student's ACT math score, ACTEnglish is a student's ACT English score, HS GPA is a student's official High school grade point average, Topics are the number of individual topics a student covered in the ALEKS online program, out of which, there are 292 topics possible to cover. Hours is the total number of hours a student spent working in the online program.

Initial regression: factors related to increase in test score. Hours inversely proportional to outcome.

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	-15.91071	10.38662	-1.53	0.1272
ACTMath	0.9680273	0.499955	1.94	0.0543
ACTEnglish	-0.420444	0.334255	-1.26	0.2099
HS GPA	4.2791736	2.496476	1.71	0.0881
Topics	0.2723753	0.030582	8.91	<.0001*
Hours	-0.189303	0.061487	-3.08	0.0024*

Figure 2. Regression output for factors related to increase in Math placement test score.

Overall, ACTMath, HS GPA, Topics and Hours are all significant contributors to the increase in a student's MPL score. Additionally, the factors Topics and Hours may have a strong correlation, and combining the two measures into topics covered per hour in the system was thought to be a better representation of outcome and would remove any possible collinearity without discounting either measure. It was also believed that the more topics a student was able to cover in the time they were in the system, the better. Figure 3 shows the results of this change.

Using topics/hour, negative correlation.

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	-13.02413	11.97417	-1.09	0.2781
ACTMath	1.6125857	0.559206	2.88	0.0044*
ACTEnglish	-0.324024	0.377941	-0.86	0.3923
HS GPA	6.4096464	2.670965	2.40	0.0174*
Topcs per hour	-12.34515	2.625835	-4.70	<.0001*

Figure 3. Revised output replacing topics and hours spent in online with the measure 'Topics per hour' for factors related to increase in Math placement test score.

The results showed a similar level of significance for each term, however a lower overall R square of only .18 v. .36 for the figure 2 regression, which supports the assumption of collinearity. Somewhat counterintuitively, the topics per hour measure returned a negative correlation to overall increase in score. This means that the greater number of topics a student passed during their time logged in, the lower their improvement. The student data set was reviewed and revealed a dramatic difference in the skew of hours and topics that students logged.

Many students were highly motivated towards the beginning of the course, putting in much more than the required 6 hours per week, some in excess of 12 hours in the first weeks of the course. Many of these students passed a high numbers of topics, then began to log far less hours as the course progressed and presumably more difficult. Given this revelation, the student weekly average hour totals were added together with an equal weight over 15 weeks, and total hours were capped at 6 per week. A new term was created, 'Weighted Avg' which is the average for each individual week with the cap at 6 hours. This resulted in the regression shown in Figure 4.

Topics is a function of ACT M, GPA, Weighted Average and an interaction

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	-57.37339	21.52251	-2.67	0.0083*
ACTMath	3.0592936	0.900975	3.40	0.0008*
HS GPA	7.2856086	5.054754	1.44	0.1511
Weighted Avg	21.338182	2.147273	9.94	<.0001*
(HS GPA-3.05564)* (Weighted Avg-3.21033)	-5.927531	3.454214	-1.72	0.0877

Figure 4. Regression output of topics covered as a function of ACT Math, HS GPA, weighted average of time logged in the system and an interaction term of HS GPA and Weighted Average

This regression showed a reduced importance of the HS GPA factor when the weighted average was added to the regression. This shows a possible contribution of HS GPA to weighted average of time in ALEKS. The regression also showed that the weighted average and ACT math were strongly linked to the increase in math placement score. The regression shown in Fig. 5 was run to determine any connection between ACT math or HS GPA and the weighted average of time in ALEKS.

Weighted average is a function of HS GPA

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	0.8345185	0.727771	1.15	0.2529
ACTMath	-0.019677	0.030835	-0.64	0.5241
HS GPA	0.8898599	0.16332	5.45	<.0001*
(ACTMath-20.6172)*(HS GPA-3.0482)	-0.037731	0.057309	-0.66	0.5110

Figure 5. Regression output, weighted average time logged in v. ACT Math, HS GPA and interaction term.

This shows that HS GPA was strongly correlated to the weighted average of time spent in ALEKS for the 15 weeks of the term. This also shows a definitive link between HS GPA and a measure that demonstrates effort, therefore achieving the first objective of this study. The 113 students with HS GPAs greater than 3.0 spent an average of 3.53 hours every week logged in the program, while the 96 students with below 3.0 HS GPAs spent only 2.66 hours. Figure 6 shows that this difference is significant by comparing the HS GPA groups weighted average with other students weighted averages using a T-test of means.

LS means differences, student's t.α=0.050 t=1.961

Hypothesized Value	2.66338
Actual Estimate	3.52619
DF	112
Std Dev	1.12703
	t Test
Test Statistic	8.1381
Prob > |t|	<.0001
Prob > t	<.0001
Prob < t	1

Figure 6. Means comparison test for students with above v. below 3.0 High School GPA

In support of Objective 1, it can be stated that HS GPA is an accurate predictor of effort in this mathematics intervention, even for far underprepared students.

Objective 2

In objective 1, it was shown that HS GPA was correlated to effort through the association of the weighted average time in the system. This also confirms objective 2, that students spend more time

in the self-paced portion of the course based on increased effort. Although there is a slight modification in semantics of this objective, *overall* effort (i.e., total time) is not highly correlated to success as much as *consistent* effort, measure by the weighted average time. With this change in thinking, Objective 2 is satisfied in terms of productive time spent logged into the self-paced segment of the course. This is also supported in terms of the APCM. In Figure 7, Support Seekers (SS) and Achievers (A), two groups proven to have higher effort (Author 1), have statistically significantly higher weighted average times in the system that the other two student types. As these two student types have above average HS GPA at a 3.0, this provides further support of the assertion that effort, as it is correlated to HS GPA, leads to greater utilization of time in the self-paced system.

APCM of Weighted Average				
LSMeans Differences Student's t				
$\alpha = 0{,}050; t = 1.961$				
Level				Least Sq Mean
SS	A			3.795
A		B		3.297
PS			C	2.751
SPS			C	2.620

Figure 7. Levels not connected by letter are statistically significant

For part two of Objective 2, it must be shown that HS GPA, or effort, leads to superior outcomes of the course in terms of testing. Figure 8 shows the connection between the increase in scores and the APCM. This table reveals that both the Achievers (A) and the Support Seekers (SS) had far greater increases in test scores over the term than the other two groups given that A has a mean of 31.3 and SS has a mean of 28.3, significantly greater than the both PS and SPS (22.7 and 18.1 respectively). Of additional interest is the high variability in performance of the PS group, which contributes to an overall lack of significant fit of the other terms, but still provides explanatory value for the model. Further discussion is presented in a subsequent section.

Objective 3

Oneway Anova					
Summary of Fit					
Rsquare	0.068451				
Adj Rsquare	0.054336				
Root Mean Square Error	19.98746				
Mean of Response	25.33663				
Observations (or Sum Wgts)	202				
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Ratio**	**Prob > F**
APCM	3	5812.357	1937.45	4.8497	0.0028
Error	198	79100.752	399.5		
C. Total	201	84913.109			
Means for Oneway Anova					
Level	**Number**	**Mean**	**Std Error**	**Lower 95%**	**Upper 95%**
A	60	31.2333	2.5804	26.145	36.322
PS	32	22.6563	3.5333	15.688	29.624
SPS	58	18.0862	2.6245	12.911	23.262
SS	52	28.2692	2.7718	22.803	33.735
Std Error uses a pooled estimate of error variance					

Figure 8. ANOVA comparing the four Academic Performance-Commitment Matrix groups for the study group.

It was shown in the previous sections that there are mixed results in terms of student outcomes. While the average student increased their math placement score significantly, the motivations utilized in the course may not have had an equal effect on all student populations. It seems that the less motivated students (PS/SPS) had much lower increases in math placement scores. While it was shown that this was primarily due to lower overall effort as measured by weighted average time in the system, this may also mean that there are insufficient incentives for this student type. More development of measures and an alternative study of incentives is necessary to fully interpret findings in relation to objective 3.

Conclusion and Discussion

The primary objective of this study was to relate the significance of high school GPA in the context of student effort in a math remediation course in engineering. To determine this effect, the study defined effort in measurable terms as consistent performance in the self-paced online support tool ALEKS. This effort was measured in a weighted average login time of up to 6 hours per week for 15 weeks. Students with higher than 3.0 HS GPAs had significantly greater effort as measured by this weighted average, and this resulted in higher overall scores on the math placement exam when retested.

To further extend the research into the predictability of effort and motivation, these findings were connected to a previous metric, the Academic Performance-Commitment Matrix, and the APCM provided a strong structure to support the conclusion that the psychosocial factors of conscientiousness, termed "effort" in this study, and motivation are readily extended to the significantly underprepared students studied here.

These findings support the efforts in enrollment management for open access admissions schools to invest recruitment resources for engineering programs into student groups that may not traditionally have been considered due to their lack of preparation as long as these students have 1) demonstrated consistent effort and 2) there exists a support program in place to assist in advancement through the rigorous curriculum. By focusing these efforts on Achievers (A) and Support Seekers (SS) will result in improved enrollment and greater overall retention rates.

What remains is the wide variability of the Purpose Seekers (PS), and the low performance of the Purpose and Support Seekers (SPS). While PS have shown the capacity to perform well, efforts to engage this group as universally as SS and A students have not been fruitful. These groups have shown low levels of motivation, and have not had consistent effort in using support tools, such as ALEKS. This has resulted in low performance in the study course, but also greater drop-out rates beyond the first semester. The academic talent among this group is high, as measured by ACT math scores, but are prone to underperforming and therefore failing at much higher rates. SPS students have a myriad of concerns, that range from low motivation, to low efficacy.

The final discussion is the overall impact on underrepresented student groups. They have disproportionately low test scores, but have a high number of SS students. This further supports the enrollment management goals this study promotes. If there is any real mission designed at increasing the participation of underrepresented groups, providing an academic remediation pathway that improves their efficacy, while also demonstrating to them that effort is a key to success is a necessary component to any academic plan. Courses that provide a self-paced component along with in-class contextual math applications may be a solution. Further research into these student groups will be conducted as population sizes allow.

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