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Factors that Predict ACT Science Scores from a Multicultural Perspective

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Abstract: *This study investigated predictors for ACT Science scores, a test used by many universities to rank applicants. This study utilized quantitative research methods using the Montana Office of Public Instruction's GEMS (Growth and Enhancement of Montana Students) data set. All advanced statistical analysis was conducted using Stata software IC/15. This research is significant for increasing the representation of under-represented groups in STEM education because it helps clarify three important relationships: (1) How well do gender, race, and meal status predict 11th grade ACT Science scores; (2) How well does school size predict 11th grade ACT Science scores while controlling for gender, race, and meal status; and (3) How well does high school GPA predict 11th grade ACT Science scores while controlling for gender, race, meal status, and school size.*

Key Words: GEMS (growth and enhancement of Montana students), ACT Science scores, regression analyses, secondary data analysis, multicultural education

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LITERATURE REVIEW

The ACT, i.e. American College Test, is a standardized high-school achievement test that colleges use to rank applicants (Bauer & Wise, 2016). The ACT includes four subjects—English, mathematics, reading, science, and an optional writing test (Frey, 2018). The ACT score is on a scale of 1-36 for each of the four subject areas with a composite score averaging the four scores and rounded to the nearest whole number (Watson & Flamez, 2014). Maruyama (2012) found that, for high school students, "ACT scores in English, math, science, and reading were related respectively to student performance in English composition, college algebra, college biology, and college social studies/humanities" (p.3).

In examining variables that predict ACT scores, researchers have identified achievement gaps based on race, socioeconomic status, and other factors. As Soares (2015) notes, race and ethnicity are important variables in predicting ACT scores. Black and Hispanic students receive

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lower average ACT scores compare to White and Asian Americans. Lotkowski, Robbins, and Noeth (2004) use High School Grade Point Average (HSGPA) and ACT Assessment scores as academic factors that predict postsecondary retention. Socioeconomic status (SES), parents' educational achievement, and family income are non-academic factors that also predict postsecondary retention. A combination of academic and non-academic factors, together, best predict postsecondary retention and performance. Inzlicht and Ben-Zeev (2000) argue that gender stereotype negatively predicts females' test performance. When it comes to test scores as well as other measures of science, math, and STEM ability, females positioned in a male dominated environment generally show lower achievement than males.

Class size is a good predictor of ACT performance. Students in small classes are more likely to take the ACT exam and they perform better than those in average-size classes, thus increasing their probability of college acceptance (Krueger & Whitmore, 2001; Schanzenbach, 2006). Small classes may not be better for all students, however. Budden & Hsing (2006) found that with small class sizes, socioeconomic status is magnified, with a larger achievement gap between poor and better-off students. Furthermore, qualified high school instructors play a significant role because such teachers provide higher quality instruction that leads to students having higher academic success. Interestingly, school size acts very differently from class size, as results from Lotkowski, Robbins, and Noeth (2004) indicate that school size has no relationship on college retention.

Some researchers question whether educational institutions should use standardized test scores for high school students to predict college success. Rooney & Schaeffer (1998) claim that standardized test scores are not the best predictors of college student success. Studies by Lotkowski, Robbins, and Noeth (2004) counter that claim, finding that ACT scores used in conjunction with other factors are good predictors of college success. Importantly, the study argued that ACT scores and other factors are excellent ways of identifying at-risk students so that colleges can improve retention, a finding that Bettinger, Evans, and Pope (2013) confirmed. Furthermore, as a core finding, Bettinger, Evans, and Pope (2013) show that the ACT composite score obscures the fact that ACT English and Math scores are strongly correlated with college success, whereas ACT Science and Reading scores are not. This study also found little correlation between ACT Science scores and either high school or college GPA.

Despite some criticism of using standardized test scores as a predictor of college success, Hays (2017) points out that Midwestern colleges use ACT tests as an important tool to make admission and financial aid decisions. In other words, whether or not ACT scores are a good predictor of achievement once students are admitted to college, their use in the admissions process means that ACT scores can be a significant factor in limiting achievement. Therefore, this research, using Montana high school students as a case study, is significant and has practical implications for high schools located in Western and Northern Rocky Mountain regions. Little research has been conducted to show what factors predict ACT Science Scores. This paper fills that gap by examining factors that predict 11th Grade ACT Science Scores for Montana high school students. It provides valuable insights for schools to better prepare their students to achieve higher ACT scores needed for college acceptance.

DESIGN AND METHODOLOGY

The purpose of this research is to investigate and determine academic and non-academic factors that predict 11th grade ACT Science scores. It is important to understand these factors so we as educators can help students excel in their studies and become college ready for Science and STEM fields. The overall intent and objectives are to examine the above relationships. The unit of analysis is 11th grade ACT Science scores. The social phenomenon is how well do public high schools prepare students for their 11th grade ACT Science tests.

The independent variables (IVs) (gender, race, meal status, school size, and high school GPA) could predict the dependent variable (DV) (11th grade ACT Science scores) for the following reasons. Gender might predict the DV because males seem to do better with science in general than females. This could be because females receive many social cues that discourage them from pursuing science fields. Race could predict the DV because White students on average have more financial and social resources compared to Non-White students. Meal status could predict the DV because it is a proxy for socioeconomic status. Low income students in general might not perform as well academically because they lack role models, i.e. no professional in their family, or parents who place less emphasis on their children's studies. They also have to struggle with non-academic issues, such as housing, food security, and health care. School size might predict the DV because larger schools have more resources to better support students. GPA could predict the DV because the two are similar as measurements of learning.

As researchers and teachers involved in higher education and STEM fields, we want to better understand student learning and develop strategies to improve student learning. 11th grade ACT Science scores are used in the research questions as a measured outcome of student learning. For the quantitative research design, the research questions, hypotheses, sample/population, variables, coding, level of measurement, and operationalization will be described in detail as follows.

Research Questions and Hypotheses

Research question #1: How well do gender, race, and meal status predict 11th grade ACT Science scores? This research question is used to examine the relationship between the three demographic independent variables (gender, race, and meal status) and the dependent variable (11th grade ACT Science scores).

Ha: Gender, race, and meal status predict 11th grade ACT Science scores.

Research question #2: How well does school size predict 11th grade ACT Science scores while controlling for gender, race, and meal status? This research question is used to examine the relationship between the independent variable of interest (school size) and the dependent variable (11th grade ACT Science scores).

Ha: School size predicts 11th grade ACT Science scores while controlling for the three demographic independent variables (gender, race, and meal status).

Research questions #3: How well does high school GPA predict 11th grade ACT Science scores while controlling for gender, race, meal status, and school size? This research question is used to examine the relationship between the independent variable (high school GPA) and the dependent variable (11th grade ACT Science) while controlling for gender, race, meal status, and school size.

Ha: High school GPA predicts 11th grade ACT Science scores while controlling for gender, race, meal status, and school size.

Population and Sample

The population is 8887 high school seniors in the 2015 – 2016 academic year who entered postsecondary education in a Montana institution in 2016 – 2017. A random sample of 300 participants was selected. Table 1 illustrates relevant demographic statistics and descriptive data of the sample characteristics.

Table 1. Descriptive Data and Demographic Statistics of the Sample Characteristics

Gender	
Males (Reference)	**144 (48.0%)**
Females	**156 (52.0%)**
Race	
Non-White	**35 (11.7%)**
White (Reference)	**265 (88.3%)**
Meal Status	
F/free (Reference)	**48 (16.0%)**
N/non-free	**238 (79.3%)**
R/reduced	**14 (4.7%)**
School Size/Class	
A (Reference)	**70 (23.3%)**
AA	**139 (46.3%)**
B	**49 (16.3%)**
C	**42 (14.0%)**
GPA	
Continuous	**0-4**
Total	**300**

As shown in Table 1, this study includes 156 females and 144 males (male is the reference group). 265 students identified themselves as White and 35 students fall into the categories classified as Non-White (White is the reference group). Forty-eight receive free lunch, 238 did not receive free lunch, and 14 received reduced cost lunch (free lunch is the reference group). Seventy are from Class A schools, 139 are from class AA, 49 are from class B, and 42 are from class C (class A is the reference group).

Study Variables

As shown in Table 2 below, for research question 1 (How well do gender, race, and meal status predict 11th grade ACT Science scores?), the independent variables are gender, race, and meal status, and they are all categorical/dummy variables. Gender is dummy coded where 0=male, and 1=female. For race, White is dummy coded as "0", all the other races including Hispanic, American Indian, Asian, two or more races are combined as Non-White due to small sample sizes and dummy coded as "1". Meal status is dummy coded where 0=free, 1=reduce, and 2=non-free. The dependent variable is 11^{th} grade ACT Science scores, the scores range from 1-36, and it is a continuous variable measured at the ratio level. 11^{th} grade ACT Science scores are used as a measure of learning.

For research question 2 (How well does school size predict 11^{th} grade ACT Science scores while controlling for gender, race, and meal status?), the independent variable is school size. A is represented as "1", B is represented as "2", C is represented as "3", and AA is represented as "4". The control variables are gender, race, and meal status. The dependent variable is 11^{th} grade ACT Science scores, the scores range from 1-36, and it is a continuous variable measured at the ratio level.

For research question 3 (How well does high school GPA predict 11^{th} grade ACT Science scores while controlling for gender, race, meal status, and school size?), the independent variable is GPA, the scores range from 0-4, and it is a continuous variable measured at the ratio level. The dependent variable is 11^{th} grade ACT Science scores, the scores range from 1-36, and it is a continuous variable measured at the ratio level.

Table 2: Study Variables

Research Question 1				
	Name	Description	Coding	Level of Measurement
Independent variable	Gender	Male & Female	Male = 0 **(Reference)** Female = 1	Categorical/Dichotomous (dummy)
Independent variable	Race	White & Non-White	White=0 (**Reference**) Non-White=1	Categorical/Nominal (dummy)
Independent variable	Meal Status	Free, Reduced & Non-free	Free=0 **(Reference)** Reduce =1 Non-free= 2	Categorical/Nominal (dummy)
Dependent variable	11^{th} grade ACT Science scores	Mean 11^{th} grade ACT Science scores	1-36	Continuous

Research Question 2				
	Name	Description	Coding	Level of Measurement
Independent variable	School Size	A, B, C, AA	A = 1 (**Reference**) B = 2 C = 3 AA= 4	Categorical/Nominal(dummy)
Dependent variable	11^{th} grade ACT Science scores	Mean 11^{th} grade ACT Science scores	1-36	Continuous

Research Question 3				
	Name	Description	Coding	Level of Measurement
Independent variable	HS GPA	Mean high school GPA	0-4	Continuous
Dependent variable	11^{th} grade ACT Science scores	Mean 11^{th} grade ACT Science scores	1-36	Continuous

Statistical Strategy

The analytical approach for this research was based on Urdan (2011), Acock (2018), and Mehmetoglu & Jakobsen (2017). Multiple regression allows for a net effect of X_1 keeping X_2 constant and X_2 = control or covariate (p.73, Mehmetoglu & Jakobsen, 2017). Multiple regressions ($Y= a + b_1X_1 + b_2X_2 + b_3X_3 + \ldots + b_iX_i$, "a" is the intercept and "b" is the unstandardized beta coefficient) were used to examine the relationship between a continuous (i.e., interval or ratio scaled) dependent variable (11^{th} grade ACT Science scores) and continuous (high school GPA) and dummy/categorical dependent variables (gender, race meal status, and school size) (Urdan, 2011).

Three Ordinary Least Squared (OLS) Regression Models were used to evaluate the three research questions and hypotheses. OLS Regression is a conceptual model and a mathematical function used to explain the relationships among variables of interest. The three models were built based on the same logic and each model was built on top of the previous model. For model 1, the dependent variable 11^{th} grade ACT Science scores was regressed on the independent variables (gender, race, and meal status). The purpose of model 1 was to test the net effect of gender, race, and meal status on the dependent variable 11^{th} grade ACT Science scores. The goal was to assess the demographic variables and how well they predict the dependent variables. For model 2, the variable of interest was added to model 1 to test the relationships between the dependent variable 11^{th} grade ACT Science scores and the independent variable school size. The additional control variable high school GPA was added for model 3 (the full model).

Research Question 1/Hypothesis 1:

Model 1: 11^{th} grade ACT Science scores= a + b1(gender)+ b2 (race) + b3 (meal status)

Research Question 2/Hypothesis 2:

Model 2: 11^{th} grade ACT Science scores = a + b1(gender)+ b2 (race) + b3 (meal status) + b4 (school size)

Research Question 3/Hypothesis 3:

Model 3: 11^{th} grade ACT Science scores = a + b1(gender)+ b2 (race) + b3 (meal status) + b4 (school size) + b5 (high school GPA)

Descriptive statistics for 11^{th} grade ACT Science scores and high school GPA are shown in Table 3. The mean for high school GPA is 3.30 and the standard deviation is 0.54. The mean for 11^{th} grade ACT Science scores is 21.9 and the standard deviation is 4.77.

Table 3: Descriptive Statistics for 11th Grade ACT Science Scores and High School GPA

```
. tabstat ACTScience11 HS_GPA, stats(mean, sd, range count)
```

stats	ACTSc~11	HS_GPA
mean	21.94333	3.309002
sd	4.771023	.5441673
range	34	2.43
N	300	300

As shown in Table 4, the normality of the variables was evaluated by skewness and kurtosis statistics.

Table 4: Skewness and Kurtosis

```
. sktest gendercoded RaceEthnicityFedCoded MealStatusCoded ClassCoded HS_GPA ACTScience11
```

Skewness/Kurtosis tests for Normality

				joint	
Variable	Obs	Pr(Skewness)	Pr(Kurtosis)	adj chi2(2)	Prob>chi2
gendercoded	300	0.5628	.	.	.
RaceEthn~ded	300	0.0000	0.0000	.	0.0000
MealStatus~d	300	0.0000	0.0178	60.88	0.0000
ClassCoded	300	0.0034	.	.	.
HS_GPA	300	0.0001	0.0311	16.68	0.0002
ACTScience11	300	0.5879	0.0071	7.20	0.0274

```
. tabstat ACTScience11 gendercoded RaceEthnicityFedCoded MealStatusCoded ClassCoded HS_GPA, statistics (Ske
> wness, Kurtosis)
```

stats	ACTSc~11	gender~d	Race~ded	MealSt~d	ClassC~d	HS_GPA
skewness	-.0749568	-.0800641	2.388201	-1.63251	-.4196527	-.5748774
kurtosis	3.975316	1.00641	6.703504	3.805793	1.522014	2.50809

Skewedness and kurtosis were tested using procedures described by Acock (2018). The test for skewness was significant ($p < 0.05$) for High School GPA indicating that it has negative skewness (GPA skewness =-0.57, p=0.000). The test for Kurtosis was significant ($p < 0.05$) for GPA and 11th grade ACT science indicating that these variables have positive kurtosis (GPA kurtosis=2.51, p=0.031; and 11th grade ACT science kurtosis=3.98, p=0.007).

Model specificity and regression residuals were tested using a series of diagnostic procedures. As shown in Table 5, there were no violations observed with heteroskedasticity, multicollinearity, specification problem, functional form, and influential observations. The normality assumption of constant residuals was tested using the Shapiro-Wilk W normality test. The findings showed the assumption for normality was violated suggesting that some of the residuals are not normally distributed. This could be due to the categorical independent variables of gender, race, meal status, and school size/class.

Table 5: Statistical Analysis (statistical tests, assumptions, and diagnostic procedures)

```
. quietly regress ACTScience11 gendercoded RaceEthnicityFedCoded MealStatusCoded ClassCoded HS_GPA

. regcheck

   Regression assumptions:                      | Test:                                        We seek value

1) no heterokedasticity problem                 | Breusch-Pagan hettest                          > 0.05
                                                | Chi2(1): 0.086
                                                | p-value: 0.769

2) no multicollinearity problem                 | Variance inflation factor                      < 5.00
                                                | HS_GPA : 1.09
                                                | MealStatusCoded : 1.07
                                                | RaceEthnicityFedCoded : 1.05
                                                | gendercoded : 1.05
                                                | ClassCoded : 1.01

3) residuals are not normally distributed       | Shapiro-Wilk W normality test                  > 0.01
                                                | z: 5.178
                                                | p-value: 0.000

4) no specification problem                     | Linktest                                       > 0.05
                                                | t: 1.112
                                                | p-value: 0.267

5) appropriate functional form                  | Test for appropriate functional form           > 0.05
                                                | F(3,291):1.404
                                                | p-value: 0.242

6) no influential observations                  | Cook's distance                                < 1.00
                                                | no distance is above the cutoff
```

PREPARING THE DATA

All data preparation used the GEMS dataset in Excel, which then was imported to Stata. Stata IC/15 was performed to analyze the data and produce the visual representation (graphs) of the data. The hypotheses were evaluated at .05 level of significance. We kept a research log that described the analytical procedures. One data preparation strategy was recoding the gender, race, meal status, school size (class) groups. Gender is dummy coded where 0=male, and 1=female. For race, White is dummy coded as "0", all the other races including Hispanic, American Indian, Asian, two or more races are combined as Non-White due to small sample sizes and dummy coded as "1". Meal status is coded where 0=free, 1=reduce, and 2=non-free. School size (class) A is coded as "1", B is coded as "2", C is coded as "3", and AA is coded as "4".

RESULTS

The descriptive statistics are shown in Table 2. Please refer to Appendix A for histograms of the independent and dependent variables and Appendix B for the scatter plot of the continuous independent variable with the dependent variable. Three OLS models were estimated to evaluate the three research questions.

Research question 1: How well do gender, race, and meal status predict 11th grade ACT Science scores? In model 1 (11th grade ACT Science scores = gender + race + meal status), multiple regression was conducted to test research question 1 to determine if the linear combination of the independent variables (gender, race, and meal status) have some explanatory power in explaining the dependent variable 11th grade ACT Science scores.

The results in Table 6 of the F-test for 11th grade ACT Science scores, regressed on gender, race, and meal status, show a significant relationship ($F(4, 295) = 5.62$, $p=0.0002$). This suggests that the linear combination of independent variables is significantly associated with 11th grade ACT Science scores. The R^2 shows that the combination of independent variables explains 7.08% of the variance in 11th grade ACT Science scores. The adjusted R^2 shows that the combination of independent variables explains 5.82% of the variance in 11th grade ACT Science scores. There is a 1.26% difference between the R^2 and the adjusted R^2.

The R^2 for model 1 is 0.07. The adjusted R^2 for this model is 0.06. The adjusted R^2 is the corrected version of the original R^2 and serves as a conservative adjustment to account for the added predictor variables (Mehmetoglu & Jakobsen, 2016). Therefore, the total variance explained by the linear combination of independent variables for 11th grade ACT Science scores is 6%.

Table 6: Model 1 Result

```
. reg ACTScience11 i. gendercoded i. RaceEthnicityFedCoded i. MealStatusCoded
```

Source	SS	df	MS		
				Number of obs =	300
				F(4, 295) =	5.62
Model	481.833698	4	120.458424	Prob > F =	0.0002
Residual	6324.20297	295	21.4379762	R-squared =	0.0708
				Adj R-squared =	0.0582
Total	6806.03667	299	22.7626644	Root MSE =	4.6301

ACTScience11	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
1.gendercoded	-.7470098	.5384337	-1.39	0.166	-1.806668	.3126483
1.RaceEthnicityFedCoded	-2.891266	.8464608	-3.42	0.001	-4.557133	-1.225399
MealStatusCoded						
1	-.1706697	1.40794	-0.12	0.904	-2.941549	2.60021
2	1.422684	.7431277	1.91	0.057	-.0398199	2.885188
_cons	21.54839	.7689828	28.02	0.000	20.03501	23.06178

The significant variable in model 1 is race (b=-2.89, p=0.001). Compared to White, Nonwhite students score 2.89 points lower on the 11th ACT Science scores.

Research question 2: How well does school size predict 11th grade ACT Science scores while controlling for gender, race, and meal status? In model 2 (11th grade ACT Science scores = gender + race + meal status + school size), we added school size as a variable of interest. Multiple regression was conducted to test research question 2 to determine if school size predicts 11th grade ACT Science scores while controlling for gender, race, and meal status.

The results in Table 7 of the F-test for 11th grade ACT Science scores, regressed on school size, show a significant result ($F(7, 292) = 4.05$, $p=0.0003$). This suggests that the linear combination of independent variables are associated with 11th grade ACT Science scores. The R^2 shows that the combination of independent variables (gender, race, meal status, and school size) explains 8.85% of the variance in 11th grade ACT Science scores. The adjusted R^2 shows that the combination of independent variables explains 6.67% of the variance in 11th grade ACT Science scores. There is a 2.18% difference between the R^2 and the adjusted R^2. The small difference between the R^2 and adjusted R^2 suggests that the new predictor variable (school size) added to the model is important.

Table 7: Model 2 Result

```
reg ACTScience11 i. gendercoded i. RaceEthnicityFedCoded i. MealStatusCoded i. ClassCoded
```

Source	SS	df	MS		
				Number of obs =	300
				F(7, 292) =	4.05
Model	602.419992	7	86.0599989	Prob > F =	0.0003
Residual	6203.61667	292	21.2452626	R-squared =	0.0885
				Adj R-squared =	0.0667
Total	6806.03667	299	22.7626644	Root MSE =	4.6093

ACTScience11	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
1.gendercoded	-.8115025	.5437116	-1.49	0.137	-1.881593	.2585879
RaceEthnicityFedCoded	-2.89793	.8448744	-3.43	0.001	-4.560746	-1.235115
MealStatusCoded						
1	-.3984726	1.416529	-0.28	0.779	-3.186373	2.389427
2	1.284566	.7500529	1.71	0.088	-.1916297	2.760761
ClassCoded						
2	-1.288084	.8651329	-1.49	0.138	-2.990771	.4146021
3	.1041843	.9050692	0.12	0.908	-1.677102	1.88547
4	.5426423	.682891	0.79	0.427	-.80137	1.886655
_cons	21.64729	.9156198	23.64	0.000	19.84524	23.44934

The significant variable is race (b=-2.90, p=0.001). Gender, meal status, and school size are not significant. Compared to White, Nonwhite students score 2.90 points lower on the 11th ACT Science scores. Between model 1 and model 2, the unstandardized coefficient for race had minimal change of 0.01 by adding the variable school size.

Research question 3: How well does high school GPA predict 11th grade ACT Science scores while controlling for gender, race, meal status, and school size. High school GPA was added in model 3 (11th grade ACT Science scores = gender + race + meal status + school size + high school GPA). Multiple regression was conducted to test research question 3 to determine if high school GPA predicts 11th grade ACT Science scores while controlling for gender, race, meal status, and school size.

The results in Table 8 of the F-test for 11th grade ACT Science scores, regressed on high school GPA, show a significant (F (8, 291) =15.49, p=0.0000). This suggests that the linear combination of independent variables are associated with 11th grade ACT Science scores. The R^2 shows that the combination of the independent variables (gender, race, meal status, school size, and high school GPA) explains 29.87% of the variance in 11th grade ACT Science scores. The adjusted R^2 shows that the combination of independent variables explains 27.94% of the variance in 11th grade ACT Science scores. There is a 1.93% difference between the R^2 and the adjusted R^2.

The R^2 shows that the combination of the independent variables (gender, race, meal status, school size, and high school GPA) explains 29.87% of the variance in 11th grade ACT Science scores, a 21.02% increase from the 8.85% explained by model 2. The adjusted R^2 shows that the combination of the independent variables (gender, race, meal status, school size, and high school GPA) explains 27.94% of the variance in 11th grade ACT Science scores, a 21.27% increase from the 6.67% explained by model 2.

Both the R^2 and the adjusted R^2 increased from model 1 to model 2 to model 3 by adding variables of interests and the control variable. The increase in adjusted R^2 occurred from model 2 to model 3 and was due to GPA. The increase from model 2 to model 3 between R^2 and adjusted R^2 was minimal.

The adjusted R^2 from model 1 to model 2 changed from 0.06 to 0.07, respectively, in the full model 3, the adjusted R^2 is 0.28. This is a marked improvement in explaining the variance in

11th grade ACT Science scores. Indeed, 28% of the variance in 11th grade ACT Science scores can be explained by the linear combination of predicted variables (gender, race, meal status, school size, and high school GPA). The marked increase in adjusted R^2 in model 3 was with the addition of GPA, suggesting that GPA is responsible for the improvement from model 2 to model 3. The adjusted R^2 were used to interpret the change in variance between the models because the adjusted R^2 is designed to overcome the weakness by taking into account the added predictors. As Minitab Editors (2015) explained in a tutorial, "The adjusted R^2 is a modified version of R^2 that has been adjusted for the number of predictors in the model. The adjusted R^2 increases only if the new term improves the model more than would be expected by chance."

Table 8: Model 3 Result

```
. reg ACTScience11 i. gendercoded i. RaceEthnicityFedCoded i. MealStatusCoded i. ClassCoded HS_GPA
```

Source	SS	df	MS			
				Number of obs	=	300
				F(8, 291)	=	15.49
Model	2032.78352	8	254.097939	Prob > F	=	0.0000
Residual	4773.25315	291	16.4029318	R-squared	=	0.2987
				Adj R-squared	=	0.2794
Total	6806.03667	299	22.7626644	Root MSE	=	4.0501

ACTScience11	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
1.gendercoded	-1.571018	.4846213	-3.24	0.001	-2.524825	-.6172105
1.RaceEthnicityFedCoded	-1.847812	.7508413	-2.46	0.014	-3.32558	-.3700443
MealStatusCoded						
1	-.4284485	1.244676	-0.34	0.731	-2.878158	2.021261
2	.2132713	.6689652	0.32	0.750	-1.103352	1.529895
ClassCoded						
2	-1.462894	.7604036	-1.92	0.055	-2.959482	.0336943
3	-.6959194	.7998665	-0.87	0.385	-2.270176	.8783375
4	.4457691	.6001308	0.74	0.458	-.7353782	1.626916
HS_GPA	4.233847	.4533908	9.34	0.000	3.341506	5.126188
_cons	8.946658	1.580215	5.66	0.000	5.836558	12.05676

The significant variables are gender (b=-1.57, p=0.001), race (b=-1.85, p=0.014), and high school GPA (b=4.23, p=0.000). Between model 2 and model 3, the unstandardized coefficient for race had a change of 1.05 by adding the variable GPA. From model 2 to model 3 when adding GPA, gender became significant (spurious intervening). Also, class C school almost became significant in model 3.

The OLS regression shows a significant negative relationship between females on 11th grade ACT Science scores compared to males. Results in Table 8 shows that a female would score 1.57 points lower than a male on their 11th grade ACT Science scores, holding all other variables constant. Compared to White students, Nonwhite students score 1.85 points lower on the 11th ACT Science scores, holding all other variables constant. There was no significant relationship between meal status/school size and 11th grade ACT Science scores. The OLS regression shows a significant positive relationship between high school GPA and 11th grade ACT Science scores. For each unit increased in GPA there is a 4.23-point increase in a student's 11th grade ACT Science scores while controlling for all other variables. The ancillary analysis was conducted to examine the interactions between gender and GPA, race and GPA, and race and gender but there were no significant interactions.

Below are three different scenarios that predict a student's 11th grade ACT Science scores.

SCENARIO 1: GENDER DIFFERENCE

SCENARIO 1A. What is the predicted 11th grade ACT Science score for a non-white ***female*** with free meals from a class C school with a GPA of 3.0?

Y = 11th grade ACT Science score
X_1 = Gender = female = 1, (reference male = 0)
X_2 = Race = Non-White = 1, (reference White = 0)
X_3 = Meal Status = free = 0, (reference free = 0)
X_4 = School Size = C = 1, (reference class A = 0)
X_5 = GPA = 3.0, (1-4)
$Y = a + b_1X_1 + b_2X_2 + b_3X_3 + b_4X_4 + b_5X_5 + b_6X_6 + b_7X_7 + b_8X_8$
11th grade ACT Science score = constant + b_1(gender)+ b_2 (race) + b_3 (reduced meal status) + b_4 (non-free meal status) + b_5 (B school size) + b_6 (C school size) + b_7(AA school size) + b_8 (high school GPA)
Y = 8.95+ (-1.57)(1) + (-1.85)(1) + (-0.43)(0) + (0.21)(0) + (-1.46)(0) + (-0.70)(1) + (0.45)(0) + (4.23)(3.0)
17.52= 8.95 - 1.57 - 1.85 - 0.70 + 12.69
The predicted value that she would receive on her 11th grade ACT Science score is 17.52.

SCENARIO 1B. What is the predicted 11th grade ACT Science score for a non-white male with free meals from a class C school with a GPA of 3.0?

Y = 11th grade ACT Science score
X_1 = Gender = male = 0, (reference male = 0)
X_2 = Race = Non-White = 1, (reference White = 0)
X_3 = Meal Status = free = 0, (reference free = 0)
X_4 = School Size = C = 1, (reference class A = 0)
X_5 = GPA = 3.0, (1-4)
$Y = a + b_1X_1 + b_2X_2 + b_3X_3 + b_4X_4 + b_5X_5 + b_6X_6 + b_7X_7 + b_8X_8$
11th grade ACT Science score = constant + b_1(gender)+ b_2 (race) + b_3 (reduced meal status) + b_4 (non-free meal status) + b_5 (B school size) + b_6 (C school size) + b_7(AA school size) + b_8 (high school GPA)
Y = 8.95+ (-1.57)(0) + (-1.85)(1) + (-0.43)(0) + (0.21)(0) + (-1.46)(0) + (-0.70)(1) + (0.45)(0) + (4.23)(3.0)
19.09= 8.95 - 1.85 - 0.70 + 12.69
The predicted value that he would receive on his 11th grade ACT Science score is 19.09.

SCENARIO 2: RACE DIFFERENCE

SCENARIO 2A. What is the predicted 11th grade ACT Science score for a non-white female with free meals from a class C school with a GPA of 4.0?

Y = 11th grade ACT Science score
X_1 = Gender = female = 1, (reference male = 0)
X_2 = Race = Non-White = 1, (reference White = 0)
X_3 = Meal Status = free = 0, (reference free = 0)
X_4 = School Size = C = 1, (reference class A = 0)

X_5 = GPA = 4.0, (1-4)
$Y = a + b_1X_1 + b_2X_2 + b_3X_3 + b_4X_4 + b_5X_5 + b_6X_6 + b_7X_7 + b_8X_8$
11th grade ACT Science score = constant + b_1(gender)+ b_2 (race) + b_3 (reduced meal status) + b_4 (non-free meal status) + b_5 (B school size) + b_6 (C school size) + b_7(AA school size) + b_8 (high school GPA)
Y = 8.95+ (-1.57)(1) + (-1.85)(1) + (-0.43)(0) + (0.21)(0) + (-1.46)(0) + (-0.70)(1) + (0.45)(0) + (4.23)(4.0)
21.75= 8.95 - 1.57 - 1.85 - 0.70 + 16.92
The predicted value that she would receive on her 11th grade ACT Science score is 21.75.

Scenario 2B. What is the predicted 11th grade ACT Science score for a white female with free meals from a class C school with a GPA of 4.0?
Y = 11th grade ACT Science score
X_1 = Gender = female = 1, (reference male = 0)
X_2 = Race = White = 0, (reference White = 0)
X_3 = Meal Status = free = 0, (reference free = 0)
X_4 = School Size = C = 1, (reference class A = 0)
X_5 = GPA = 4.0, (1-4)
$Y = a + b_1X_1 + b_2X_2 + b_3X_3 + b_4X_4 + b_5X_5 + b_6X_6 + b_7X_7 + b_8X_8$
11th grade ACT Science score = constant + b_1(gender)+ b_2 (race) + b_3 (reduced meal status) + b_4 (non-free meal status) + b_5 (B school size) + b_6 (C school size) + b_7(AA school size) + b_8 (high school GPA)
Y = 8.95+ (-1.57)(1) + (-1.85)(0) + (-0.43)(0) + (0.21)(0) + (-1.46)(0) + (-0.70)(1) + (0.45)(0) + (4.23)(4.0)
19.37= 8.95 - 1.57 - 0.70 + 16.92
The predicted value that she would receive on her 11th grade ACT Science score is 23.60.

Scenario 3: Meal Status Difference

Scenario 3A. What is the predicted 11th grade ACT Science score for a non-white female with free meals from a class C school with a GPA of 2.0?
Y = 11th grade ACT Science score
X_1 = Gender = female = 1, (reference male = 0)
X_2 = Race = Non-White = 1, (reference White = 0)
X_3 = Meal Status = free = 0, (reference free = 0)
X_4 = School Size = C = 1, (reference class A = 0)
X_5 = GPA = 2.0, (1-4)
$Y = a + b_1X_1 + b_2X_2 + b_3X_3 + b_4X_4 + b_5X_5 + b_6X_6 + b_7X_7 + b_8X_8$
11th grade ACT Science score = constant + b_1(gender)+ b_2 (race) + b_3 (reduced meal status) + b_4 (non-free meal status) + b_5 (B school size) + b_6 (C school size) + b_7(AA school size) + b_8 (high school GPA)
Y = 8.95+ (-1.57)(1) + (-1.85)(1) + (-0.43)(0) + (0.21)(0) + (-1.46)(0) + (-0.70)(1) + (0.45)(0) + (4.23)(2.0)
14.69= 8.95 - 1.57 - 1.85 - 0.70 + 9.86
The predicted value that she would receive on her 11th grade ACT Science score is 14.69.

Scenario 3B. What is the predicted 11th grade ACT Science score for a non-white female with non-free meals from a class C school with a GPA of 2.0?

Y = 11th grade ACT Science score
X_1 = Gender = female = 1, (reference male = 0)
X_2 = Race = Non-White = 1, (reference White = 0)
X_3 = Meal Status = non-free = 1, (reference free = 0)
X_4 = School Size = C = 1, (reference class A = 0)
X_5 = GPA = 2.0, (1-4)
$Y = a + b_1X_1 + b_2X_2 + b_3X_3 + b_4X_4 + b_5X_5 + b_6X_6 + b_7X_7 + b_8X_8$
11th grade ACT Science score = constant + b_1(gender)+ b_2 (race) + b_3 (reduced meal status) + b_4 (non-free meal status) + b_5 (B school size) + b_6 (C school size) + b_7(AA school size) + b_8 (high school GPA)
Y = 8.95+ (-1.57)(1) + (-1.85)(1) + (-0.43)(0) + (0.21)(1) + (-1.46)(0) + (-0.70)(1) + (-0.45)(0) + (4.23)(2.0)
14.90= 8.95 - 1.57 - 1.85 +0.21 - 0.70 + 9.86
The predicted value that she would receive on her 11th grade ACT Science score is 14.90.

Discussion and Analysis of Data

For research question 1, the results indicate that the demographic variable race predicts 11th grade ACT Science scores. White students have higher 11th grade ACT Science scores compared to Non-White students. Gender and meal status are not significant in predicting 11th grade ACT Science scores. In the OLS regression analysis using the same data set, gender and meal status were significant in predicting 12th grade ACT STEM scores. It is an interesting comparison because it is possible that males with higher socioeconomic status (SES) are more interested in pursuing STEM majors and careers. Often, a student's SES is indicated by their eligibility (an income-based qualification) to qualify for free or reduced cost lunch. Therefore, males with higher socioeconomic status are more motivated to do better in taking the subject specific ACT STEM exam during their 12th grade before entering college rather than taking the general ACT exam which includes the ACT science during their 11th grade.

For research question 2, the results indicate that school size is not significant in predicting 11th grade ACT Science scores when controlling for gender, race, and meal status. This largely confirms findings from the literature. Our findings in model 2 are similar to model 1 with the addition of school size. Compared to White, Non-White students score 2.90 points lower on their 11th grade ACT Science scores. White students might have more access to educational opportunities, for example tutoring or after school science clubs, which would help explain why race is significant in predicting 11th grade ACT Science scores.

For research question 3, the results show that high school GPA can predict 11th grade ACT Science scores when controlling for gender, race, meal status, and class. We use high school GPA as the control factor as it was found in the literature review that students with higher GPA will also have higher ACT scores. In the last model, when adding GPA, gender and race are significant in predicting scores, males scored 1.57 points higher compared to females. GPA explains 21.02% more of the variance compare to model 2. High school GPA has more practical significance on predicting 11th grade ACT Science scores than race, gender, meal status, and class. This is an especially significant finding because it disagrees with the results from Bettinger, Evans, and Pope (2013), which showed little or no correlation between high school GPA and ACT Science scores.

Clearly, this finding merits further investigation. There are a number of related factors to be investigated. For example, students with a high GPA could score higher grades in other courses relative to their science grades, possibly because they have little interest in science or a STEM career. Consequently, there could be even stronger predictors of 11th grade ACT Science scores, such as high school science grades.

Conclusions and Limitations

This correlational study opens up fertile ground for research into additional variables that predict ACT performance. The lead author has tutored high school students to prepare them for their ACT exams. Thus, we are especially interested to see if taking an ACT preparation course would be an important factor for improving 11th grade ACT science scores. Unfortunately, the GEMS data set does not provide data for this variable. Another possible important variable, also not included in the GEMS data, could be parents' education levels or whether parents aided the students with their schoolwork. A final variable that the data set doesn't include is the parent's education or positive parental role models. All of these variables are important topics for future study. As a correlational study, however, it may not offer strong evidence of causality and caution is advised when making inferences about the results.

High schools and individual teachers are expected to help students improve their 11th grade ACT Science scores. By examining ACT data and associated variables, future educators and researchers can develop teaching and learning strategies to improve students' overall 11th grade ACT Science scores. Ideally this would be particularly helpful for students from diverse backgrounds (gender, race, meal status, school size, etc) who are underrepresented in STEM fields. Though this paper focused on the factors in available data that predict ACT Science scores and identify achievement gaps, it opens up possibilities for additional ways in which we can improve student performance and better prepare students for college. In better understanding predictors of ACT scores, educators can embrace many strategies. These include becoming culturally attuned to students' cultural background and social identity (race, class, age, ability, religion, gender, sexuality, language, etc), and respecting multiple intelligences through culturally responsive teaching (Ashlee & Ashlee, 2015; Brazill, 2015; Brazill, 2016; Howe & Lisi, 2013). As educators, we can also help close the achievement gaps by providing resources for tutoring and counselling services, holding high expectations for every student, advocating for equitable funding for students, and insuring that curriculum materials are relevant and accessible to students. And, finally, students need to see their personal stories reflected in the curriculum (Howe & Lisi, 2013).

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