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ABSTRACT

This study was an examination of the usefulness of a statistical regression approach to identify prospective Engineering and Information and Computer Science (ICS) applicants most likely to succeed at the University of California at Irvine (UCI). The specific purpose was to determine the extent to which preadmissions measures such as high school grade point average (GPA) and admissions test scores could be used to predict college GPA. Multiple regression was used to maximize the correlation between the criterion variable (GPA) and predictor variables (preadmissions measures). Results indicate that cumulative GPA and major GPA of the presented samples of UCI Engineering and ICS majors can be reliably predicted using a linear combination of two preadmissions measures: high school GPA and the College Board Mathematics Achievement Test. None of the other three predictor variables (Scholastic Aptitude Test-Mathematics, Scholastic Aptitude Test-Verbal, and the College Board English Composition Achievement Test) added significantly to the predictions. Some shrinkage in the size of multiple correlations is expected when the equations of this study are applied to subsequent samples. However, in general, colleges that use the SAT and the high school record to predict freshmen GPA generally find that the results are fairly stable from year to year. (PN)

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PREDICTING CUMULATIVE AND MAJOR GPA

OF UCI ENGINEERING AND COMPUTER SCIENCE MAJORS

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PREDICTING CUMULATIVE AND MAJOR GPA OF UCI ENGINEERING AND COMPUTER SCIENCE MAJORS

This prediction study was initiated by the University of California, Irvine's Office of Undergraduate Admissions to determine appropriate admissions policies for oversubscribed majors at UCI. Oversubscribed majors are those in which the number of eligible freshmen applications exceeds the number that can be enrolled. Currently there are two oversubscribed majors at UCI: Engineering (ENG) and Information and Computer Science (ICS). While UC has a general policy of accepting every eligible applicant, it may not be possible to admit every eligible student in his/her first choice of major on a particular campus. In the case of oversubscribed majors, each campus adopts its own supplementary procedures admission, following broad guidelines established by UC. The current study was an examination of the usefulness of a statistical regression approach to identify those prospective Engineering and ICS applicants who would be most likely to succeed at UCI.

The specific purpose of this study was to determine the extent to which preadmissions measures such as high school grade point average (GPA) and admissions test scores could be used to predict college GPA. If a strong relationship was found for past UCI students, then the preadmissions measures of current applicants could be used to predict their UCI GPA's and thus estimate their chances of success at UCI. This problem was studied using the technique of multiple regression which maximizes the correlation between a given criterion variable (college GPA) and certain predictor variables (preadmissions measures). The size of the multiple correlation, which varies between zero and one, indicates the extent to which the criterion can be predicted using a linear combination of the predictors.

In this study two criterion variables were selected: cumulative GPA and major GPA. Both of these were measured at the end of the sophomore year at UCI. The five predictor variables were: high school GPA in the UC required pattern of "A-F" courses, verbal and quantitative scores from the Scholastic Aptitude Test, and achievement test scores from the College Board Mathematics Achievement Test (Level 1 or 2) and the English Composition Achievement Test.[1]

Engineering and ICS majors were analyzed separately. For each criterion variable, the following questions were of interest:

1. Can the criterion variable be reliably predicted using a linear combination of the predictors?

2. What is the fewest number of variables needed to reliably predict the criterion? What are these variables?

3. Can the criterion variable be reliably predicted using a linear combination of the predictors for subgroups of students?

4. What is the fewest number of variables needed to reliably predict the criterion for subgroups? What are these variables?

5. Are there any significant differences in the obtained multiple correlations across independent subgroups?

6. To what extent can the overall regression equation, obtained using the entire sample, predict subgroup means?

METHOD

Subjects

Two cohorts of UCI Engineering and ICS students were combined across years to increase the sample sizes for subgroup analyses. The first cohort group entered UCI as freshmen in fall quarter 1980 and were still enrolled at UCI in spring quarter 1982. The second cohort entered as freshmen in fall 1981 and were still enrolled in spring 1983. Students were classified as Engineering or ICS majors if they had declared majors in either the School of Engineering or the Department of Information and Computer Science for at least one quarter during their freshmen or sophomore years. The sample was restricted to those Engineering and ICS majors who had scores on all the variables in the study.

For analysis purposes, the two majors were further divided into subgroups: men, women, Educational Opportunity Program[2] (EOP) students, Student Affirmative Action[3] (SAA) students, Asians,[4] and Whites. EOP and SAA students are eligible for special state- and University-funded programs which are designed to improve their chances of success in college and are therefore of special interest in this study. Ethnicity information was taken from the student's UC application.

Variables

Two criterion variables were chosen for this study: (1) sophomore cumulative GPA (CUMGPA), and (2) sophomore major GPA (MAJGPA). The major GPA included grades from all service courses required for Engineering or ICS, not just those courses in the major subjects, including mathematics for ICS majors and mathematics, physical science, and chemistry for Engineering majors. UCI course grades can range from 4.00 (A) to 0.00 (F) with partial credit for plus and minus grades (e.g., A- = 3.67).

Five predictor variables were used: (1) high school GPA from courses taken after the ninth grade in the UC-specified "A-F" pattern of course and verified by transcripts (AFGPA), (2) SAT-V, (3) SAT-M, (4) the College Board Mathematics Achievement Test, either Level 1 or 2 (MATHACH), and (5) The College Board English Composition Achievement Test (ENGACH). The SAT and College Board scores have a maximum range of 200-800 with a theoretical population mean of 500 and standard deviation of 100. High school GPA had a maximum value of 4.00 (no extra points awarded for honors courses).

Analytical Procedures

The method of analysis chosen for this study was multiple regression which optimizes the correlation between the criterion (college GPA) and a linear combination of the predictors (high school GPA and admissions test scores). The linear combination of predictors, and its associated weights for each of the predictors, is designed to yield the highest possible correlation with the criterion. The "best" regression equation was defined, in this study as the one in which the multiple correlation coefficient R is significantly different from zero and which contains the fewest number of predictors (that is, additional variables do not significantly improve the value of R^2).

A total of 28 (2 majors X 2 criterion variables X 7 subgroups) stepwise regressions were calculated using SPSS (Release 8) on UCI's PRIME. A maximum of five regression equations (five predictors) were generated for each of the 28 conditions. The stepwise regression procedure used by SPSS follows the forward selection procedure (See Pedhazur, 1982, p. 154) in which the first variable to enter the equation is the one with the highest zero-order correlation (r) with the criterion variable, the second is the one with the highest partial correlation with the criterion after partialing out the variable already in the equation, and so on.

Three of the maximum of five stepwise regression equations were of interest in this study: (1) the equation with only one variable, the single best predictor, (2) the "optimal" or best equation with one to four variables in which the addition of another variable would not add significantly to the prediction, and (3) the equation with all five variables or the full model. These three equations were compared for differences in their ability to predict the criterion.

Three statistics were calculated for each regression equation: (1) the multiple correlation coefficient R, (2) R^2 or the amount of criterion score variance that can be accounted for or explained by the linear combination of predictors, and (3) the standard error of estimate (SE) which is in criterion score (GPA) units. The SE can be used to determine the accuracy of the prediction equation. Two-thirds of the time on the average, we would expect the actual GPA of an individual to be within one SE of the predicted GPA; ninety-five percent of the time it would be within two SE's of the predicted GPA. The weights in each regression equation can be examined to determine the relative contribution of each variable to the linear prediction. When unstandardized weights were calculated, each regression equation also contained a constant (C).

To determine if the prediction equations were statistically significant, each R^2 was tested against zero following Pedhazur (1982, p. 57). The significance test used to determine the optimal regression equations was a test in the increment in R^2 due to the addition of the next variable (Pedhazur, 1982, p. 62). Regression equations from independent subgroups were compared by testing differences in R's using the Fisher Z transformation (Reynolds, 1982, p. 209). The significance level for each test was set at .05.

RESULTS

Means, Standard Deviations, and Intercorrelations

Tables 1 and 2 contain the means and standard deviations for all variables in the study for all groups and subgroups. In the Engineering sample, 21% were women and 79% were men. In the ICS sample, 44% were women and 56% were men. The self-reported ethnicity of the Engineering majors was: 28% White, 25% Asian, 14% SAA (American Indian, Black, Chicano, Latino, or Pilipino), and 33% Other or not reported. The ethnicity of ICS majors was: 52% White, 31% Aisan, 10% SAA, and 7% Other or not reported.

Engineering and ICS majors had almost identical mean scores on the preadmissions measures. Their mean high school GPA's were quite similar (ENG = 3.64 and ICS = 3.62) and were almost one standard deviation above the nation mean high school GPA of 3.06 (standard deviation = .60) as reported by all students taking the SAT in 1980 and 1981 (College Bound Seniors, 1980, 1981).

For both majors, the mean SAT-M scores (ENG = 598 and ICS = 596) were considerably higher than the mean SAT-V scores (454 for both ENG and ICS). The national means, averaged over 1980 and 1981 for comparability with the UCI samples, were 466 for the SAT-M and 424 for the SAT-V.

The mean achievement test scores show the same pattern as the aptitude test scores, with the means on the Mathematics Achievement Test considerably above the means on the English Composition Achievement Test. Again, there were virtually no differences between the two majors on either achievement test. The 1980/81 national average for those students who elected to take the Mathematics Achievement Test (either Level 1 or Level 2) was 596; the national average for the English Composition Achievement Test was 515. Thus the UCI means were virtually identical with the national average on the Mathematics Test but slightly below the national average on the English Composition Test.

The same pattern of differences between quantitative and verbal tests can be seen across the various subgroups. The largest differences between verbal and quantitative scores were found for Asian students. For Asian Engineering majors these differences were statistically significant (using one-tailed t tests between SAT-M and SAT-V and between the two achievement tests). For Asian ICS students there was a significant difference between mean SAT scores, but not between mean achievement test scores.

On the two criterion variables, cumulative and major GPA, the ICS major received slightly higher UCI grades, on the average, then did the Engineering majors. Compared to high school GPA's, the UCI GPA's for both majors were consistently lower (about .80 lower) and twice as variable.

Table 3 contains the first order correlations among the variables for all Engineering and ICS majors. The correlation matrices for subgroups showed similar patterns and are not repeated here. Inspection of the correlation matrices indicates there is considerable intercorrelation or high multicolinearity among the predictor variables, especially between the two quantitative tests (SAT-M and Mathematics Achievement) and between the two verbal tests (SAT-V and English Composition Achivement Test). High multicolinearity poses several problems in multiple regression (see Pedhazur, 1982, p. 232). For instance, high intercorrelations make variables redundant. Thus after one is entered into equation, the second may not be able to make any further contribution to the prediction. This can lead to reversals of the signs of weights and other interpretation problems.

The following sections describe the results of the stepwise regression procedures for Engineering and ICS majors.

Engineering Majors

Cumulative GPA. Table 4 contains the stepwise regression results for predicting the sophomore cumulative GPA of Engineering majors. The best predictor is the Mathematics Achievement Test which has a correlation of .52 with cumulative GPA. Using the Mathematics Achievement Test alone accounts for 28% of the criterion score variance. The standard error of estimate is .47 grade points.

The optimal equation contains only two of the five predictor variables. The addition of high school GPA significantly improves the prediction of cumulative GPA over using the Mathematics Achievement Test alone. The addition of the three other predictor variables did not add significantly to the equation. The optimal equation increases the multiple correlation to .62, has a standard error .44 grade points, and accounts for 38% of the criterion score variance.

Table 4 also contains the results obtained when all five predictors are entered into the equation. This equation is presented for comparison purposes only since the addition of the last three variables did not significantly improve the amount of prediction, nor did any of the statistics (R, R^2 or SE) change more than .01. The high multicolinearity among predictors may be contributing to the negative weights in the full regression equation.

The optimal regression equations for each of the six subgroups of engineering majors are presented in Table 5. All of the subgroup multiple R's were significantly different from zero. When multiple R's from independent groups were compared, there were no significant differences.

For all subgroups, cumulative GPA could be reliably predicted using at most one or two predictors. For five of the subgroups, these variables were the Mathematics Achievement Test alone or in combination with the high school GPA. The only exception was the SAA subgroup; their best predictor was the English Composition Achievement Test. The small size of the SAA sample may have contributed to the non-significance of additional predictors.

The overall regression equation, based on the full sample of Engineering majors, was applied to each of the subgroups. The predicted subgroup means were all within .06 grade points of the obtained means. There were slight overpredictions for men, SAA students, and Whites, and slight underpredictions for women, EOP students, and Asians.

Cumulative GPA for Engineering majors can, then, be reliably predicted (R=.62) using a linear combination of the Mathematics Achievement Test and high school GPA, plus a constant:

CUMGPA = .59694(AFGPA) + .00264(MATHACH) - .98639 (ENGINEERING)

This equation has a standard error of estimate of .44 grade points and explains 38% of the criterion score variance. The addition of SAT-M, SAT-V, and the English Composition Achievement Test did not significantly improve the prediction. There were no significant differences in multiple R's across independent subgroups. For each subgroup, at most two variables were needed to predict cumulative GPA. Using the overall regression equation did not seriously affect the accuracy of the predictions for subgroups.

Major GPA. Table 6 contains the stepwise regression results for predicting sophomore major GPA for Engineering majors. The best predictor is the Mathematics Achievement Test which has a correlation of .55 with the criterion. It accounts for 31% of the variance of major GPA and has a standard error of estimate of .55 grade points.

In the optimal equation, high school GPA adds to the Mathematics Achievement Test to produce a multiple correlation of .62 with major GPA. Together these two variables explain 38% of the criterion score variance and reduce the standard error to .52 grade points. The addition of subsequent variables did not significantly improve the prediction.

There were virtually no changes in R, R^2 or the SE when all five predictor variables were included. Again, the negative weights in the full model are probably related to the problem of high multicolinearity among the predictors.

Results for subgroups are presented in Table 7. The multiple R's were all significantly different from zero. For all subgroups, the single best predictor was the Mathematics Achievement Test. The second significant predictor was high school GPA. There were no significant differences in multiple R's across independent subgroups.

The overall regression equation was used to predict subgroup means. All of the predicted means were within .08 grade points of the obtained means. There were slight overpredictions for women, SAA students, and Whites, and underpredictions for EOP students and Asians. There were no differences in means for men.

The major GPA of engineering majors can, then, be reliably predicted (R=.62) using a linear combination of the Mathematics Achievement Test and high school GPA; plus a constant:

MAJGPA = .59999(AFGPA) + .00350(MATHACH) - 1.60200 (ENGINEERING)

This equation explains 38% of the criterion score variance and has a standard error of .52 grade points. Additional predictors did not significantly improve the prediction. There were no significant differences in multiple R's across independent subgroups. The most powerful predictor for all subgroups was the Mathematics Achievement Test. The overall prediction equation fairly accurately predicted scores for subgroups.

Computer Science Majors

Cumulative GPA. Table 8 contains the results of the stepwise regression procedure for predicting the sophomore cumulative GPA of ICS majors. High school GPA was the best predictor of cumulative GPA with a correlation of .41 which accounts for 17% of the criterion score variance. The standard error of estimate using high school GPA alone was .45 grade points.

The optimal regression equation adds the Mathematics Achievement Test to high school GPA. The two-variable equation increases the multiple correlation to .51 and explains 26% of the criterion score variance. The standard error is reduced to .43 grade points.

Although the addition of subsequent predictors did not significantly improve the prediction, the results with all five predictors are presented in Table 8 for comparison purposes. The addition of three more variables did not change the multiple R, R^2 or the standard error of estimate. The negative weights in full model are probably due to the high multicolinearity among predictors and to the fact that none of the last three variables are adding a reliable amount to the prediction equation.

Table 9 contains the optimal regression equations for each of the six subgroups of ICS majors. The multiple R's for all subgroups, except SAA students, were significantly different from zero. There were no significant differences among the multiple correlations when independent groups were compared. Cumulative GPA could be reliably predicted with at most two variables: high school GPA alone or in combination with the Mathematics Achievement Test or SAT-M.

Using the overall regressional equation to predict subgroup means resulted in predicted mean GPA's within .13 grade points of the observed means. The overall regression equation overpredicted for men, EOP students, and SAA students, and underpredicted for women and Whites. There was no difference between predicted and obtained means for Asians using the overall regression equation.

Cumulative GPA, then can be reliably predicted (R=.51) for this sample of ICS majors using a linear combination of high school GPA and the Mathematics Achievement Test, plus a constant:

CUMGPA = .50266(AFGPA) + .00155(MATHACH) + .13139 (ICS)

This equation accounts for 26% of the criterion score variance and has a standard error of .43 grade points. The addition of SAT scores and the English Composition Achievement Test did not improve the prediction of cumulative GPA. Among independent subgroups, there were no significant differences in the multiple correlations. At most, two variables were needed to reliably predict cumulative GPA for the subgroups. The overall regression equation predicted subgroup means fairly accurately.

Major GPA. Table 10 contains the stepwise regression results for predicting sophomore major GPA for ICS majors. The best predictor of major GPA is the Mathematics Achievement Test score with a correlation of .51. When used alone, this variable accounts for 25% of the criterion score variance and has a standard error of .56 grade points.

The optimal regression equation is a statistically significant improvement over the use of the Mathematics Achievement Test alone. Together these two variables increase the multiple correlation to .58 while reducing the standard error of estimate to .53 grade points. The optimal equation accounts for 34% of the criterion score variance. Additional variables did not significantly improve the prediction.

For comparison purposes, the regression equation with all five predictors is included in Table 10. The addition of these variables only slightly affected the multiple R, R^2 and the standard error. Again, the negative weights are probably due to the high multicolinearity among the predictors plus the non-significant contribution of the variables added after the first two.

Table 11 contains the optimal regression equations for each of the six subgroups of computer science majors. The multiple R's for all subgroups were significantly different from zero. Comparing independent subgroups, there were no significant differences in the magnitude of the multiple R's. For five of the subgroups, major GPA could be reliably predicted using at most two variables: high school GPA alone or in combination with the Mathematics Achievement Test or SAT-M. For women computer science majors, a third variable, SAT-V, made a significant contribution to the prediction.

Applying the overall optimal regression equation to each of the subgroups resulted in predicted mean GPA's for the subgroups within .17 grade points of the obtained means. The largest difference was an overprediction of .17 grade points for the SAA mean. There were overpredictions for men and Whites, and underpredictions for women, EOP students, and Asians.

We can conclude, then, that major GPA for this sample of ICS majors can reliably predicted (R=.58) using a linear combination of high school GPA and the Mathematics Achievement Test, plus a constant:

$$\text{MAJGPA} = .55617(\text{AFGPA}) + .00299(\text{MATHACH}) - 1.05756 \qquad \text{(ICS)}$$

This equation accounts for 34% of the criterion score variance and has a standard error of estimate of .53 grades points. Adding SAT-M, SAT-V and the English Achievement Test did not significantly improve the prediction. There were no significant differences in multiple R's among independent subgroups. Applying the overall regression equation to the subgroups did not significantly alter predicted subgroup means.

DISCUSSION OF THE RESULTS

The results of this study indicate that cumulative GPA and major GPA of these samples of UCI Engineering and ICS majors can be reliably predicted using a linear combination of two preadmissions measures: high school GPA and the Mathematics Achievement Test. None of the other three predictor variables (SAT-M, SAT-V, English Composition Achievement Test) added significantly to the predictions. Thus, only two of the five preadmissions measures contributed significantly to the predictions.

For Engineering majors, the single best predictor of both cumulative and major GPA was the Mathematics Achievement Test, followed by high school GPA. None of the other variables added significantly to the predictions. Both criterion scores could be predicted to the same extent; that is, the multiple correlations for cumulative and major GPA were both equal to .62.

For ICS majors, major GPA was slightly more predictable than cumulative GPA (R=.58 compared to R=.51). For cumulative GPA, the high school GPA was the single best predictor, followed by the Mathematics Achievement Test. For major GPA the relative importance of these two predictors was reversed; the Mathematics Achievement Test was the best predictor, followed by high school GPA. No other variables significantly improve the predictions.

Cumulative and major GPA can also be reliably predicted by for subgroups of Engineering and ICS majors with at most two variables, with the one exception of predicting major GPA of women ICS majors. The two variables that consistently appeared in the subgroup equations were again the Mathematics Achievement Test and the high school GPA. Since there were no significant differences in R's across independent groups, we can conclude that the UCI GPA's of all subgroups were equally predictable. Using the overall regression equation to predict subgroup means did not appreciably affect the subgroup predictions. Thus, it is not necessary to use separate regression equations for each subgroups.

The magnitude of the multiple correlations found in this study compare favorably to median correlations across similar studies (see Breland, 1979; Ford and Campos, 1977). However, very few studies have examined the predictive power of the achievement tests. Similarly, there have been very few studies conducted within major fields, despite the fact that such studies have been strongly recommended (Breland, 1979).

The applicability of these results to subsequent samples of Engineering and ICS majors needs to be demonstrated by cross--validation studies. It is to be expected that there will be some shrinkage in the size of the multiple correlations when the equations of this study are applied to subsequent samples. However, the College Board has found that, in general, colleges which use the SAT and the high school record to predict freshmen GPA generally find that the results are fairly stable from year to year. Cross-validation studies should also be conducted to determine if the same prediction patterns are observed across subgroups and to confirm or discount some of the anomalies observed with the smaller groups. Use of the overall regression equation for subgroups should also be re-examined within the context of over- and underprediction for certain groups.

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FOOTNOTES

[1]The University of California requires each applicant to submit test scores from either the Scholastic Aptitude Test or the American College Testing program, plus scores from three College Board achievement tests. Two of the achievement tests must be Mathematics (level 1 or 2) and English Composition.

[2]EOP students must meet low income requirements and/or have membership in one of the SAA groups.

[3]SAA students are defined by UC to include: American Indians, Blacks, Chicanos, Latinos, and Pilipinos.

[4]Asians include Chinese, East Indians, Japanese, Koreans, Polynesians, and other Asians, excluding Pilipinos.

Table 1

Mean Scores for Engineering Majors

Group	n		AFGPA	SAT-M	SAT-V	MATHACH	ENGACH	CUMGPA	MAJGPA
			VARIABLES						
All	296								
		M	3.64	598	454	603	469	2.77	2.69
		SD	.32	86	119	86	113	.55	.66
Women	62								
		M	3.74	576	469	578	487	2.81	2.65
		SD	.31	89	110	93	111	.42	.65
Men	234								
		M	3.61	604	450	610	464	2.76	2.70
		SD	.32	84	121	83	113	.59	.67
EOP	96								
		M	3.55	527	369	578	397	2.69	2.59
		SD	.36	94	117	87	102	.58	.70
SAA	41								
		M	3.50	529	426	529	427	2.46	2.30
		SD	.37	99	94	83	96	.49	.67
Asian	74								
		M	3.64	608	382	621	408	2.89	2.83
		SD	.32	82	128	82	97	.63	.71
White	84								
		M	3.66	614	512	611	524	2.76	2.67
		SD	.30	71	77	76	90	.50	.60

Table 2

Mean Scores for Information and Computer Science Majors

Group	n		VARIABLES						
			AFGPA	SAT-M	SAT-V	MATHACH	ENGACH	CUMGPA	MAJGPA
All	238								
		M	3.62	596	454	596	472	2.87	2.74
		SD	.33	92	129	97	110	.49	.65
Women	104								
		M	3.65	556	416	556	439	2.87	2.66
		SD	.33	88	133	90	114	.45	.62
Men	134								
		M	3.59	627	483	626	498	2.88	2.79
		SD	.33	82	117	91	100	.52	.68
EOP	65								
		M	3.52	547	347	557	382	2.75	2.56
		SD	.38	91	128	100	104	.47	.65
SAA	23								
		M	3.51	514	476	527	467	2.58	2.12
		SD	.40	94	99	91	83	.41	.56
Asian	74								
		M	3.66	594	364	598	411	2.90	2.83
		SD	.34	92	139	102	120	.53	.61
White	123								
		M	3.60	617	508	609	514	2.93	2.81
		SD	.32	83	89	90	86	.46	.64

Table 3

Intercorrelations Between Variables for Engineering and ICS Majors

Variable		2	3	4	5	6	7
ENGINEERING MAJORS (n = 296)							
1.	AFGPA	.27	.25	.34	.30	.48	.45
2.	SAT-M	--	.40	.79	.44	.43	.45
3.	SAT-V		--	.30	.81	.21	.18
4.	MATHACH			--	.39	.52	.55
5.	ENGACH				--	.30	.27
6.	CUMGPA					--	.92
7.	MAJGPA						--
ICS MAJORS (n = 238)							
1.	AFGPA	.23	.15	.24	.25	.41	.39
2.	SAT-M	--	.44	.82	.49	.35	.48
3.	SAT-V		--	.40	.85	.23	.16
4.	MATHACH			--	.45	.39	.51
5.	ENGACH				--	.26	.23
6.	CUMGPA					--	.86
7.	MAJGPA						--

Table 4

Stepwise Regression Equations
for Cumulative GPA of Engineering Majors (n = 296)

Equation	k[a]	R	R^2	SE	Var	r	Weights[b] B	Weights[b] Beta	Percent Contribution
Single Predictor	1	.52	.28	.47	MATHACH	.52	.00339	.52416	100%
							C = .72789[e]		
Optimal Equation[c]	2	.62	.38	.44	MATHACH	.52	.00264	.40730	54
					AFGPA	.48	.59694	.34669	46
							C = -.98639		
Full Model[d]	5	.62	.39	.44	MATHACH	.52	.00232	.35800	37
					AFGPA	.48	.58527	.33991	35
					ENGACH	.30	.00063	.12745	13
					SAT-V	.21	-.00051	-.10840	11
					SAT-M	.43	.00029	.04461	5
							C = .97837		

[a] k = number of variables in the equation.

[b] B weights are unstandarized; beta weights are standarized.

[c] Increment in R^2 due to addition of next variable was not significant ($p > .05$).

[d] Full model uses all 5 predictor variables.

[e] C = constant for the unstandardized equation.

NOTE: Optimal equation significantly improves prediction over single predictor; full model does not add significantly to optimal equation.

Table 5

Optimal Regression Equations[a] for Cumulative GPA of Engineering Subgroups

Group	*n*	*R*	R^2	*SE*	Var	Percent Contribution
Women	62	.48	.23	.58	MATHACH	100%
Men	234	.65	.42	.45	MATHACH AFGPA	57 43
EOP	96	.61	.37	.46	MATHACH AFGPA	67 33
SAA	41	.59	.34	.40	ENGACH	100
Asian	84	.64	.41	.49	MATHACH AFGPA	62 38
White	143	.62	.38	.39	AFGPA MATHACH	62 38

[a] Increment in R^2 due to addition of next variable was not significant ($p > .05$).

Table 6

Stepwise Regression Equations
for Major GPA of Engineering Majors (n = 296)

Equation	k^a	R	R^2	SE	Var	r	Weights[b] B	Beta	Percent Contribution
Single Predictor	1	.55	.31	.55	MATHACH	.55	.00426	.55186	100%
							C = .12103[e]		
Optimal Equation[c]	2	.62	.38	.52	MATHACH	.55	.00350	.45331	61
					AFGPA	.46	.59999	.29236	39
							C = -1.60200		
Full Model[d]	5	.62	.39	.52	MATACH	.55	.00316	.40930	42
					AFGPA	.46	.60282	.29374	30
					SAT-V	.18	-.00068	-.12285	13
					ENGACH	.27	.00057	.09754	10
					SAT-M	.45	.00042	.05456	6
							C = .97799		

[a] k = number of variables in the equation.

[b] B weights are unstandarized; beta weights are standarized.

[c] Increment in R^2 due to addition of next variable was not significant ($p > .05$).

[d] Full model uses all 5 predictor variables.

[e] C = constant for the unstandardized equation.

NOTE: Optimal equation significantly improves prediction over single predictor; full model does not add significantly to optimal equation.

Table 7

Optimal Regression Equations[a] for Major GPA of Engineering Subgroups

Group	n	R	R^2	SE	Var	Percent Contribution
Women	62	.48	.23	.58	MATHACH	100%
Men	234	.66	.43	.51	MATHACH	58
					AFGPA	42
EOP	96	62	.38	.56	MATHACH	70
					AFGPA	30
SAA	41	.57	.33	.56	MATHACH	100
Asian	84	.64	.41	.55	MATHACH	61
					AFGPA	39
White	143	.59	.35	.53	AFGPA	51
					MATHACH	49

[a] Increment in R^2 due to addition of next variable was not significant ($p > .05$).

Table 8

Stepwise Regression Equations
for Cumulative GPA of ICS Majors (n = 238)

Equation	k[a]	R	R^2	SE	Var	r	Weights[b] B	Weights[b] Beta	Percent Contribution
Single Predictor	1	.41	.17	.45	AFGPA	.41	.61308	.41268	100%
							C = .65671[e]		
Optimal Equation[c]	2	.51	.26	.43	AFGPA	.41	.50266	.33835	53
					MATHACH	.39	.00155	.30532	47
							C = .13139		
Full Model[d]	5	.51	.26	.43	AFGPA	.41	.50129	.77343	42
					MATHACH	.39	.00117	.23055	30
					SAT-V	.23	.00035	.09103	12
					SAT-M	.35	.00038	.07108	9
					ENGACH	.26	-.00020	-.04381	6
							C = .77390		

[a] k = number of variables in the equation.

[b] B weights are unstandarized; beta weights are standarized.

[c] Increment in R^2 due to addition of next variable was not significant ($p > .05$).

[d] Full model uses all 5 predictor variables.

[e] C = constant for the unstandardized equation.

NOTE: Optimal equation significantly improves prediction over single predictor; full model does not add significantly to optimal equation.

Table 9

Optimal Regression Equations[a] for Cumulative GPA of ICS Subgroups

Group	n	R	R^2	SE	Var	Percent Contribution
Women	104	.51	.26	.43	AFGPA SAT-M	62% 38
Men	134	.54	.30	.44	MATHACH AFGPA	53 47
EOP	65	.38	.14	.44	AFGPA	100
SAA	23	.33[b]	.11	.40	AFGPA	100
Asian	74	.51	.26	.46	AFGPA SAT-M	54 46
White	123	.55	.30	.39	AFGPA MATHACH	52 48

[a] Increment in R^2 due to addition of next variable was not significant ($p > .05$).

[b] R was not significantly different from zero ($p > .05$).

Table 10

Stepwise Regression Equations for Major GPA of ICS Majors (n = 238)

Equation	k[a]	R	R^2	SE	Var	r	Weights[b] B	Weights[b] Beta	Percent Contribution
Single Predictor	1	.51	.26	.56	MATHACH	.51	.00346	.51169	100%
							C = .66705[e]		
Optimal Equation[c]	2	.58	.34	.53	MATHACH	.51	.00299	.44310	61
					AFGPA	.39	.55617	.28177	39
							C = -1.05756		
Full Model[d]	4	.59	.35	.53	MATHACH	.51	.00217	.32201	36
					AFGPA	.39	.55543	.28140	31
					SAT-M	.48	.00140	.19557	22
					SAT-V	.16	-.00049	-.09561	11
							C = -1.17911		

[a] k = number of variables in the equation.

[b] B weights are unstandarized; beta weights are standarized.

[c] Increment in R^2 due to addition of next variable was not significant ($p > .05$).

[d] In the full model, only 4 predictors entered the equation with the SPSS default for adding another variable pet at F = .01.

[e] C = constant for the unstandardized equation.

NOTE: Optimal equation significantly improves prediction over single predictor; full model does not add significantly to optimal equation.

Table 11

Optimal Regression Equations[a] for Major GPA of ICS Subgroups

Group	n	R	R^2	SE	Var	Percent Contribution
Women	104	.59	.35	.51	SAT-M	47%
					AFGPA	35
					SAT-V	19
Men	134	.60	.36	.55	MATHACH	62
					AFGPA	38
EOP	65	.56	.32	.54	SAT-M	52
					AFGPA	48
SAA	23	.56	.32	.48	AFGPA	100
Asian	74	.64	.40	.46	SAT-M	61
					AFGPA	39
White	123	.56	.32	.53	MATHACH	64
					AFGPA	36

[a] Increment in R^2 due to addition of next variable was not significant ($p > .05$).