Predictors of Persistence and Success in an Engineering Program

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This study identifies student variables that predict persistence and success in an undergraduate engineering program. Three logistic models were developed that predicted the probability of persisting successfully. Significant predictors included both cognitive and noncognitive variables; students who did well in science and mathematics courses and who were genuinely interested in engineering were more likely to persist and succeed. Predictor variables were not constant over time but changed as students progressed through the first two years of study, with performance in prerequisite science and mathematics courses emerging as the best predictors. The authors briefly discuss academic advising implications.

Our study arose from two interrelated problems in engineering education: (a) national attrition rates of approximately 50% (Hayden & Halloway, 1985) and (b) the academic advising provided to engineering students, which we have characterized as both inappropriate and inadequate (Levin & Wyckoff, 1990b).

Students are most likely to do well academically and make sound educational decisions when they clearly understand how interest, ability, and academic performance fit with a chosen field of study. When educational plans are unduly influenced by nonpersonal external factors, the risk of inappropriate planning is increased significantly. This situation exists with many students who choose engineering programs based upon employment opportunities, monetary rewards, and status. Such motives, especially when coupled with lack of ability and interest in mathematics and science, and when compounded by misconceptions about the curriculum and the profession, are not likely to support persistence and success. We attribute much attrition to inappropriate educational planning.

Academic advising may be a means to address attrition. As early as 1940 "better counseling" was cited as a need in the selection process for engineering students (Sackett, 1940). More recently, the need to improve academic advising for engineering students has been stressed (Wankat, 1986). However, the current state of academic advising for engineering students is inappropriate because it does not address the specific characteristics of individual students that relate to persistence and success in engineering and is inadequate because information on individual student characteristics is not available to advisors (Levin & Wyckoff, 1990a).

Consequently, advising focuses on course requirements for specific engineering majors and pays little attention to individual interest, ability, or appropriateness. In our opinion the present approach to academic advising in general, and engineering advising in particular, is not student centered and is intuitive, unsystematic, and founded upon assumptions rather than empirical findings (see, for instance, Badiali, Higginson, Levin, & Wyckoff, 1990).

Although engineering retention is a national issue, few studies have addressed a wide range of both student cognitive and noncognitive variables related to persistence and success in engineering. Research has not provided guidelines for identifying students at risk for attrition (Hayden & Halloway, 1985). Most research has focused on a limited number of cognitive variables as they relate to academic success and attrition (Rezak, 1988). The fact that it was more difficult to predict persistence than academic performance suggested that studying noncognitive variables might improve prediction of both persistence and success (Dorio, Kildow, & Slover, 1980). Althoughresearchers have examined some noncognitive variables (Beronja & Bee, 1986; Foster, 1976; Lent, Brown, & Larking, 1986; Marks, 1970; Taylor & Hanson, 1972; Wyckoff, 1982), not until 1988 did our comprehensive analysis examine a broad range of both cognitive and noncognitive variables (Levin & Wyckoff, 1988).

Purpose

We sought to identify predictors of persistence and success in engineering at the beginning of the junior year by analyzing 10 cognitive and 9 noncognitive student variables (see Table 1). Such predictors could provide academic advisors an empirical base and enhance academic advising for students considering engineering majors.

TABLE 1
Description of Independent Variables

Variables	*Description*	*Measurement Level*
Cognitive		
High School GPA (HSGPA)	Converted GPA based on high school academic courses only	Continuous variable (0 to 4)
Scholastic Aptitude Test score—Mathematics		Continuous variable (200 to 800)
Scholastic Aptitude Test score—Verbal		Continuous variable (200 to 800)
Algebra score (ALG)	Subscore on university placement test	Continuous variable (0 to 32)
Chemistry score (CHEMS)	Subscore on university placement test	Continuous variable (0 to 20)
Calculus I grade (CALC I)		A to F
Calculus II grade (CALC II)		A to F
Physics I grade (PHYS I)		A to F
Physics II grade (PHYS II)		A to F
Chemistry I grade (CHEM I)		A to F
Noncognitive		
Gender (GEN)		• Male • Female
Attitude toward high school mathematics	Student's reaction to high school mathematics	• Like • Dislike
Attitude toward high school physics	Student's reaction to high school physics	• Like • Indifferent/dislike
Attitude toward high school chemistry	Student's reaction to high school chemistry	• Like • Indifferent/dislike
College study hours	Anticipated college study hours per week	Continuous variable (0 to 60)
Nonscience points (FOCUS)	Focus of science interests measured by assignment of points to majors of interest	Continuous variable (0 to 100)
Reason for engineering choice (REAS)	Intrinsic (genuine) vs. extrinsic (superficial) reasons	• Genuine • Superficial
Certainty	Expressed certainty regarding intended major	• Very certain • About 50/50 • Slightly uncertain • Uncertain
Knowledge of intended major	Accuracy of student's knowledge of engineering model	• Accurate • Inaccurate

Procedures

We studied a sample (n = 1043) of 65% of entering engineering freshmen (N = 1605) at a large, mid-Atlantic research university in the fall of 1984. We assumed the sample to be random because no procedures systematically eliminated students from the study. We collected data from admission records, student responses to a self-report inventory, interviews conducted by trained professional advisors, student transcripts, and registrar records.

Table 1 describes the 19 independent variables. The dependent variable was persisting successfully in engineering at the beginning of the junior year, which we defined as having been offered admittance and having chosen to enroll in an engineering major. To be offered admittance the student must have earned a grade point average (GPA) of 2.0 or better in the engineering foundation courses of Calculus I and II, Physics I, and Chemistry I and a cumulative GPA of 2.5 or better (A = 4.0).

We analyzed the dependent variable in terms of logit models. The models predicted the log odds or probability of successful persistence in engineering to all other enrollment statuses. This ratio was estimated as a linear combination of 19 independent variables. The models were built using the CATMOD procedure with maximum-likelihood estimation (Statistical Analysis System, 1985). The significance level for entry into the model was set at p = .05.

Results

At the beginning of the junior year 510 students (48.9%) were in an engineering major (71 of 176 females or 40.3% and 439 of 867 males or 50.6%). Table 2 shows enrollment status at the beginning of the junior year.

We built three logit models and each resulted in significant predictor variables. Model I used preenrollment data. Model II used data typically available at the end of the freshman year (including preenrollment data). Model III used data typically available at the end of the sophomore year (including preenrollment and freshman data).

Model I: Preenrollment Variables Predicting Success at the Beginning of the Junior Year

The logistic regression model that best predicted the log odds of success included 6 of the 14 eligible independent variables (Table 3). In order of contribution to the total chi-square, these were (a) high school GPA, (b) algebra subscore on the university placement test, (c) gender, (d) focus of science interests measured by assignment of points to majors of interest, (e) chemistry subscore on the university placement test, and (f) reason for choosing engineering.

Model II: End-of-Freshman-Year Variables Predicting Success at the Beginning of the Junior Year

The logistic regression model that best predicted the log odds of success included 3 of the 17 eligible independent variables (Table 4). In order of contribution to the total chi-square, these were grades in (a) Physics I, (b) Calculus I, and (c) Chemistry I.

Model III: End-of-Sophomore-Year Variables Predicting Success at the Beginning of the Junior Year

The logistic regression model that best predicted the log odds of success included 3 of the 19 eligible independent variables (Table 5). In order of contribution to the total chi-square, these were grades in (a) Calculus II, (b) Physics II, and (c) Physics I.

TABLE 2
Enrollment Status by Gender at the Beginning of the Junior Year

Status	*n*	*%*	*Male*	*%*	*Female*	*%*
Continuing in baccalaureate engineering	510	48.9	439	50.6	71	40.3
Continuing (not in baccalaureate engineering)	290	27.8	224	25.8	66	37.5
Noncontinuing baccalaureate (associate degree, nondegree, dropped, withdrew)	243	23.3	204	23.5	39	22.2
Total	1043	100.0	867	100.0	176	100.0

TABLE 3
Model I—Regression for Persisting in Engineering Successfully vs. Other Enrollment Status at the Beginning of the Junior Year

Effect	*df*	*Estimate*	χ^2	*p*
Intercept	1	–4.665	44.73	.0001***
HSGPA	1	0.751	14.63	.0001***
ALG	1	0.055	10.97	.0009***
GEN	1		10.07	.0015**
Male		0.314		
Female		–0.314		
FOCUS	1	–0.016	8.85	.0029**
CHEMS	1	0.053	6.82	.0090**
REAS	1		5.93	.0149*
Genuine		0.223		
Superficial		–0.223		

*** $p \leq .001$
** $p \leq .01$
* $p \leq .05$

TABLE 4
Model II—Logistic Regression for Persisting in Engineering Successfully vs. Other Enrollment Status at the Beginning of the Junior Year

Effect (Grade)	*df*	*Estimate*	χ^2	*p*
Intercept	1	–0.731	9.25	.0024**
PHYS I	2		72.55	.0001***
A/B		1.046		
C		0.130		
D/F		–1.176		
CALC I	2		32.39	.0001***
A/B		0.744		
C		–0.084		
D/F		–0.660		
CHEM I	4		24.46	.0001***
A		1.082		
B		0.648		
C		0.169		
D		–0.720		
F		–1.179		

*** $p \leq .001$
** $p \leq .01$

TABLE 5
Model III—Logistic Regression for Persisting in Engineering Successfully vs. Other Enrollment Status at the Beginning of the Junior Year

Effect	*df*	*Estimate*	χ^2	*p*
Intercept	1	0.016	0.01	.9350
CALC II	2	0.751	38.34	.0001***
A/B		0.918		
C		0.174		
D/F		−1.092		
PHYS II	4		35.95	.0001***
A		1.479		
B		0.874		
C		0.241		
D		−0.618		
F		−1.976		
PHYS I	2		7.58	.0226*
A/B		0.459		
C		0.083		
D/F		−0.542		

*** $p \leq .001$
* $p \leq .05$

Discussion

Typically, we assume that engineering students have higher Scholastic Aptitude Test scores and high school GPAs than any other curricular cohort entering the university. However, for approximately 50% of these students something is inappropriate about the choice of engineering. This becomes obvious only after college studies begin because doing well in engineering is not a function of academic ability only or of interest only. Instead, both adequate ability and genuine interest must interact for successful persistence.

The three models that predicted qualifying for and enrolling in the College of Engineering indicate that predictive variables are not constant over time. As students progress through the first two years of college and more academic data become available, predictive variables are replaced by others of greater predictive value.

For a student who had not yet begun college, of the predictive variables, the three cognitive ones (high school GPA and the algebra and chemistry subscores on the placement test) reflected both general academic achievement and achievement in mathematics and science. Such variables are well established predictors of academic performance in science-oriented programs (Dorio et al., 1980; Ellis, 1985; Wyckoff, 1982). These typically reflect the use of ability over time, which is influenced by such personal characteristics as motivation, attitude, and study habits. These findings support a commonly held belief that the best predictor of future behavior is past behavior. However, in this study these variables were predicting not only academic performance but also a student's decision to enroll in the College of Engineering, demonstrating persistence along with success. Although academic performance may contribute to a student's decision to persist in a given major, there are always students who do not persist despite achieving at high levels.

Of note were the significant contributions of three noncognitive variables (gender, focus of science interests, and reason for choosing engineering). After controlling for all other variables, males had positive predictor estimates while females had negative predictor estimates. This was indicated by the almost 10% difference in attrition (Table 2). The determinants of this finding are unclear.

A student's focus of interest in science programs was a significant predictor variable. Students whose interests were completely focused on science curricula had higher predicted probabilities of successful persistence in engineering.

This was consistent with studies that found focused interest in science was related to (a) persistence in science-oriented curricula (Marks, 1970), (b) freshman engineering persistence and success (Levin & Wyckoff, 1988), and (c) GPA in engineering foundation courses (Levin & Wyckoff, 1988).

Finally, if a student's reason for choosing an engineering program of study was genuine (intrinsic), the probability of success increased. Students who chose engineering because they were interested in mathematics, science, and problem solving were more likely to persist and achieve at higher levels than those who chose it because of anticipated employment opportunities, money, and status.

Models II and III: Preenrollment Variables and College Performance

Our finding that predictive variables were not constant over time was expected. Predictive preenrollment variables in Model I were all replaced by academic performance variables in Models II and III as a student progressed through the first two years. In a previous study of the same cohort, the same preenrollment variables predicted GPA in engineering foundation courses taken in the first year (Levin & Wyckoff, 1988). Students possessed the greatest probability of success when they achieved As and Bs in calculus, physics, and chemistry. Cs had essentially no predictive weight, and Ds and Fs had negative predictive weights.

Implications for Academic Advising

Academic advising is widely believed to be important in student retention. Given (a) engineering programs' attrition rates, (b) the possibility of shortages in the profession (National Research Council, 1985; National Science Foundation, 1987), and (c) underrepresentation of women and minorities (Council on Research and Technology, 1989; National Science Board, 1989; National Science Foundation, 1992a, 1992b), academic advising takes on increased importance (Levin & Wyckoff, 1988, 1990a; Wankat, 1986; Woodside & Snyder, 1989).

We contend that the goal of academic advising is to assist students to make informed decisions regarding educational alternatives. Such decisions increase the likelihood of fit between a student's personal characteristics and a chosen curriculum. Such congruence increases the probability that students will persist and be successful. Informed decision making occurs when students understand relevant personal variables, relevant educational variables, and the relationship between them. A congruent informed decision exists when this fit occurs and the student understands this (Levin & Hussey, 1992).

Students are at risk when educational decisions are incongruent (Rezak, 1988). Risk increases when decisions are both incongruent and uninformed. Students are more likely to make high-risk decisions when advising has not been informed by research on student and program variables related to persistence and success. When such information is not available, students and advisors operate at an intuitive level, which may put students at risk (Levin & Wyckoff, 1990a).

Our findings reduce the potential for high-risk decisions by identifying variables that predict persistence and success, allowing us to make assessment statements about a student's degree of congruence with engineering. These assessment statements, in the form of probabilities of persisting successfully in engineering, are the solutions of the three logistic regression equations derived from our three models (Levin & Wyckoff, 1990b).

Future Research

We suggest future research in several directions. The differential rate of persisting successfully between males and females is unexplained. For example, what are the differences between academically successful women who leave engineering and those who remain? How do social and environmental variables affect this choice? Why do proportionately fewer academically qualified women than men choose engineering?How are preenrollment variables related to predictors that emerge later? In addition, the complex interaction between persistence and academic performance needs additional study. For example, why do some successful students not persist while others do?

How would more sophisticated measures, especially in noncognitive areas, improve predictability? For example, our preliminary investigations show that existing scales that measure student attitudes toward mathematics (Fennema & Sherman, 1976) can differentiate students in relation to their educational plans (Levin & Wyckoff, 1991).

Finally, attention needs to be directed to ways in which the findings of this study can be best used in academic advising to facilitate informed educational planning. This has begun with the development of a prototype academic advising model that employs this study's findings (along with other empirically derived data) in the design of advising objectives and strategies (Levin & Hussey, 1993).

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