DOCUMENT RESUME

ED 310 164 TM 013 826

AUTHOR	Ritchey, Ferris J.; Lewis, Barbara Lawhon
TITLE	A Statistical Interaction Model for Examining Compensatory Effects on Academic Performance.
SPONS AGENCY	Department of Education, Washington, DC.
PUB DATE	Nov 86
NOTE	46p.; Paper presented at the Annual Meeting of the Mid-South Educational Research Association (15th, Memphis, TN, November 19-21, 1986).
PUB TYPE	Reports - Research/Technical (143) -- Speeches/Conference Papers (150)
EDRS PRICE	MF01/PC02 Plus Postage.
DESCRIPTORS	*Academic Achievement; *College Students; Computer Uses in Education; Disadvantaged Youth; Dropouts; *Educationally Disadvantaged; *Grade Prediction; Grades (Scholastic); Higher Education; *High Risk Students; Performance Factors; Predictive Measurement; Predictive Validity; *Predictor Variables; Statistical Analysis
IDENTIFIERS	*Automatic Interaction Detector

ABSTRACT

A 2-year study of 206 college students at an urban research university in a southern state examined personal, environmental, academic, and non-academic predictors of: (1) course grade performance; and (2) academic retention. Of particular interest were "high-risk" or "disadvantaged" students and how they compensated for their marginal educational preparedness. Data sources included two student questionnaires, instructor grade records, and student transcript records for the subsequent 2 years. Automatic Interaction Detection, developed by J. A. Sonquist et. al. (1973), was used to search for interaction effects. The technique revealed that the relationship between course performance and predictor variables differed for advantaged and disadvantaged students. As was consistent with previous research, personal academic factors accounted for a significant increase in grade performance, and environmental factors tended to affect disadvantaged students more than others. Analysis of retention rates revealed reading comprehension ability to be the best predictor. The implications of the findings are discussed with reference to institutional interventions. Two tables and two figures present study data. (Author/SLD)

A Statistical Interaction Model for Examining Compensatory Effects on Academic Performance*

by

Ferris J. Ritchey, Ph.D.

Department of Sociology

and

Barbara Lawhon Lewis, Ph.D.

Department of Curriculum and Instruction

School of Education

University of Alabama at Birmingham

* Presented to the Mid-South Educational Research Association's Annual Meeting, Memphis, Tennessee, November 20, 1986. The authors would like to acknowledge the assistance of Caroline Cody, Cathy Vedder , Mary Ann Dreyspring, Brenda Serio and Charlene Sexton. This research was funded by a grant from the U.S. Department of Education.

Running head: COMPENSATORY EFFECTS ON ACADEMIC PERFORMANCE

A Statistical Interaction Model for Examining Compensatory Effects on Academic Performance

Abstract

A two-year study of 206 college students examined personal, environmental, academic, and nonacademic predictors of (a) course grade performance and (b) academic retention. Of particular interest were "high-risk" or "disadvantaged" students and how they compensated for their marginal educational preparedness. Automatic Interaction Detection (Sonquist, Baker, & Morgan, 1973) was used to search for interaction effects and revealed that the relationship between course performance and predictor variables differed for advantaged and disadvantaged students. Consistent with previous research, personal academic factors accounted for a significant increase in grade performance, and environmental factors tended to affect disadvantaged students more than others. Analysis of retention rates revealed reading comprehension ability to be the best predictor. The implications of the findings are discussed with reference to institutional interventions.

A Statistical Interaction Model for Examining Compensatory Effects on Academic Performance

The quality of education in the United States has become a major issue in the 1980s with an abundance of national studies revealing the elementary and secondary education systems to have inadequately prepared our youth for college (c.f., National Commission on Excellence in Education, 1983; Boyer, 1984). Many students enter college today ill-prepared and this is reflected in low student retention rates. Long-term resolution of this problem will require complex social and political, as well as educational, solutions. In the interim, many colleges and universities must settle for flexible admission policies. Under these conditions, the challenge of maintaining the quality of instruction while serving an increasing number of academically underprepared students becomes significant. This challenge is compounded on urban, commuter campuses with high percentages of "nontraditional" students--students who do not live on campus, who work full- or part-time, or who attend college only intermittently. In general, nontraditional students become only marginally involved in both the academic and social environments of the campus, and their academic performance and persistence are affected by factors other than those directly related to their academic competencies.

Among studies of high-risk, disadvantaged, and nontraditional students the focus has been on the correlates of retention/ persistence as well as grade point average (Nisbet, Ruble, & Schurr, 1982; Kulik, Kulik, & Shwalb, 1983; Carney & Geis, 1981; Peng & Fetters, 1978; Eagle, 1982; Rovezzi-Carroll & Thompson, 1980; Fox, 1986; Getzlaf, Sedlacek, Kearney, & Blackwell, 1984). Variables hypothesized to predict these outcomes have tended to distinguish between (1) academic and nonacademic factors, and (2) between personal (internal) and environmental (external) factors. Figure 1 classifies four types of predictor variables along these

---

Figure 1 about here

---

two dimensions. Personal academic variables may be conceived of as raw materials--intellectual and behavioral skills--a student brings to the college environment and how these are used to the student's advantage or disadvantage. Personal nonacademic variables are the background, personality, economic, and situational factors that may enhance or impede the student's ability to succeed. Academic environment variables have to do with general educational environment, type of campus, and the quality and availability of remedial, guidance, and support services. Nonacademic environment variables are those affecting students' social integration with peers.[1]

A number of studies have explored multivariate causes of student performance outcomes, and many have focused on high-risk groups. These studies explain student performance in terms of what Bean and Metzner (1985) call compensatory interactions: various factors mediate the effect of, or compensate for, less positive factors. These models suggest that environmental factors (type of campus, student subculture) and personal attributes (life situations, role conflicts, and life crises) may affect performance in different ways for students of various levels of academic competence, and that empirical relationships might be multiplicative and interactive, not merely additive. For example, Bean and Metzner (1985) examined older, part-time students who were less likely to have environmental supports and found them to have intermittent and less intense interaction with both faculty and peers. They found also that for nontraditional students, environmental supports compensated for weak academic supports, but not vice versa. They noted that their findings were similar to those of Staman (1980) who found grade average to be positively related to persistence for students under age 22, but unrelated for those over 22. Erickson, Kimmel, Murphy, and Newcomer (1976) and Greer (1980) found older students more likely to drop out of college than traditional students in spite of having earned equivalent or better grades. Pascarella and Terenzini (1983) tested Tinto's (1975) hypothesis of interaction effects between social and academic integration, and institutional and goal commitment. Academic integration influenced retention of students with low levels of social integration but had less influence for those highly socially integrated.

In sum, a review of the literature (as well as casual observation) indicates that there is no simple profile of "the successful student"; there are many ways to succeed and successful students have assorted personal characteristics. The patterns may be especially varied on nontraditional campuses. Clearly, academically advantaged students have different obligations, trials, outlooks, and degrees of success than disadvantaged students. For well-equipped students, college courses represent opportunities and challenges, because these students' personal attributes are suited to institutional demands. The institution is structured for advantaged students and, thus, facilitates successful responses from them; success feeds on success. Furthermore, advantaged students are likely to succeed in spite of a relatively poor external environment because their personal abilitites compensate for external deficiencies. In contrast, for disadvantaged students, the same curriculum and courses may be perceived as insurmountable obstacles. The incongruence between environmental demands and these students' limited abilities to respond may result in perceptions of the same external environment as a set of psychologically depressing hurdles, and predispositions to failure often result in self-fulfilling prophecies. A meaningful intervention strategy, then, should address the question: What can be done to compensate for academic and other disadvantages? In empirical research, such "compensatory factors" may be detected by an examination of statistical interaction effects.[2]

The primary purpose of the present study is to search for such interaction effects on student grade performance using a statistical procedure called Automatic Interaction Detection (AID; Sonquist et al., 1973) which will be described in detail below. Variables hypothesized to predict grade performance are selected personal characteristics, both academic and nonacademic. Environmental factors are held somewhat constant, but left unmeasured, in that a single campus is the site of the study. A secondary purpose of the study is to examine retention rates over a two year period (1984-86). The AID procedure is valuable in focusing on the specific factors affecting the performance and retention of academically disadvantaged students, and the findings are discussed in terms of targetting remedial program interventions to their specific needs. Houston and Schmidt (1987) used a modified form of AID in predicting student retention and noted that interaction techniques provide a "prediction process that can account automatically for variable interaction and thereby enhance classification and/or predictive efficiency for large samples with numerous predictor variables" (p. 28).

Methods

Sampling and Data Sources

Data were gathered from four introductory level classes, one each of anthropology, political science, psychology, and sociology at a major urban research university in a Southern state. The campus housed a medical center and health professional schools as well as post-graduate programs. The setting was a commuter campus with many nontraditional (older, full-time employed) students.

Data sources included two student questionnaires, instructor grade records, and student transcript records for the subsequent two years. The first questionnaire was administered at the start of the initial term of the study, the second, in the last regular class period of the initial term. Data from student records included admissions tests scores and grade point average at the start of the study and for the subsequent nine academic quarters. The specific predictor variables derived from these data sources are described and operationalized below.

We view this study as a preliminary effort because survey sample design and the selection of predictor variables were influenced by factors beyond our control. Courses were selected to accomplish the objectives of a larger project; thus, the sample was one of convenience rather than random. Because the sample was not administered campus-wide, expectedly it was found not to be representative of the entire student population. Nursing, social science students, and students with undeclared majors were overrepresented and engineering students were underrepresented. The generalizability of the sample was further influenced by incomplete data. The first questionnaire was completed by 338 students, but the second by only 236 because of course withdrawals or absences on the day the second questionnaire was administered. An additional 30 students failed to take final exams. In summary, 206 students completed the course and both questionnaires. A comparison of this sample to those who failed to complete the course revealed that the latter were predominantly low-GPA students. Thus, the sample may have excluded many subjects who were of particular interest to the study--"disadvantaged" students. Although we were not able to make highly generalizable statements about the entire student body, we were able to make intergroup comparisons and establish the importance of interaction effects. Our findings appeared valid since they corresponded to those found in research at other postsecondary institutions. The significance of this research is not only in its substantive results, but also in its demonstrating the need for interaction models and the utility of the AID procedure.

Operational Definitions

Student Performance. Student performance was measured by a variable we call "Standardized Grade Score" (SGS) computed from numerical grades supplied by the four instructors. It was necessary to standardize numerical grades in order to control for substantial differences in grading procedures and class means.[3] The SGS was computed as the Z-score, the number of standard deviations from the course mean a given student's numerical score fell (Ott, Larson, & Mendenhall, 1983, p. 166). Thus, SGS assessed a student's academic performance relative to the average score in the course.

The grade for a single course was chosen as the main outcome variable, rather than overall Grade Point Average (GPA), for two reasons. (See Goldman & Slaughter, 1976, for a discussion of the low criterion validity of GPA as a measure of academic performance.) One, this holds constant a number of variables which are difficult to control such as the variety and nature of requirements among diverse academic majors. For instance, some disadvantaged students nevertheless maintain high college GPAs, at least early in their academic careers, by selecting easy courses, while highly competent students' majoring in demanding technical fields (engineering, natural sciences) may experience a decline in GPA. Two, the length of time in school varied; thus, some students had GPAs established over only one or two quarters, while others had been in school longer. Given the relatively small sample size, it was not possible to sort these varied patterns of generating overall GPA. Finally, by using similar courses on an introductory level, many course-specific factors were held constant.

Retention Rates. Retention rates were based on a student registering for courses over the i .tial term and the following nine. A student was scored as having been retained in school when he or she had attended at least four academic quarters including one of the last two and/or was graduated. There were very few ambiguous cases. Most students who dropped out did so after receiving academic warnings for poor grades. Most retained students attended all quarters ir the regular nine-month academic years.

Personal Academic Predictors of Student Pe-formance.

1. GPA was recorded from student transcripts as the numb · of quality points earned per credit hour on a four point scale (A = 4 points ... D = 1 point per hour). Since some students' GPAs would be based on as few as six credit hours while others on as many as 121, criterion validity needed to be established. To do this, trends in GPA were examined for the ten quarter study period and it appeared that GPAs tended to be stable.[4]

2. American College Testing Service (ACT) composite score and the total score for the comprehension subtest of the Stanford Diagnostic Reading Test, Level 3, (SDRT) were recorded for the 129 and 96 records, respectively, for which they were available.

(These data were not available for all students because admissions tests were not required of transfer students.)

3. Reading Comprehension was computed as the proportion of correctly filled blank spaces in a CLOZE exercise, a 250-word passage with every fifth word left blank, extracted from course texts (Taylor, 1953).

4. Written Summarization Skills were assessed by analyzing student summaries of a narrative paragraph. Summaries were rated on a four point scale by two raters and the mean of their scores was used. If a discrepancy of more than one point occurred between them, a third rater scored the summary and the mean of the three ratings was used.

5. Causal Inference Ability was measured with the following item (scored 0 = incorrect, 1 = correct, answer b):

> Medical discoveries and widespread advances in sanitation have improved health and prolonged life spans and thus have lowered death rates. But birth rates have not gone down proportionately. Which of the following is the <u>effect</u>, or result, of other statements in the passage?
>
> (a) Medical discoveries and widespread advances in sanitation have improved health and prolonged life.
>
> (b) Death rates have lowered.

(c) Birth rates have not gone down proportionately.

6. Course Specific Comprehension was a measure of whether course contents were suited to student capabilities. The score was derived from a factor analysis scale computed from the following questionnaire items scored in Likert (1932) fashion:[5]

(a) The text(s) had enough diagrams, graphs, illustrations and pictures for clarification of material (1 = strongly disagree, 2 = disagree slightly, 3 = don't know, 4 = agree slightly, 5 = strongly agree).

(b) I was able to keep up with the workload in this course (1 = strongly disagree,... 5 = strongly agree).

(c) I have difficulty in picking out the important points of a reading assignment--points that later appear on an exam (1 = strongly agree, 2 = agree slightly, 3 = don't know, 4 = disagree slightly, 5 = strongly disagree).

(d) Compared to most courses I have had at [name of school], I found this one to be extremely difficult (1 = strongly agree,... 5 = strongly disagree).

(e) I did not have problems understanding course material (1 = strongly disagree,... 5 = strongly agree).

This scale had a Cronbach's Alpha reliability coefficient of.67 (Cronbach, 1951).

7. Prior Knowledge of Course Material was measured by evaluating the relevance of a list of topics the student expected the course to cover (1 = not relevant, 2 = moderately relevant, 3 = very relevant).

8. Intensity of Study Habits was a factor analysis score computed from the following items:

(a) Did you prepare written outlines of chapters in the text (1 = no, not at all; 2 = yes, for a few chapters; 3 = yes, for most chapters; 4 = yes, for all chapters)?

(b) Did you prepare written summaries of the chapters in the text (1 = no, not at all; 2 = yes, for a few chapters; 3 = yes, for most chapters; 4 = yes, for all chapters)?

(c) For this course, I always read textbook material before going to class (1 = strongly disagree,... 5 = strongly agree).

(d) I used a well-organized system of study for this course (1 = strongly disagree,... 5 = strongly agree).

(e) I outlined the chapters of the text for this course (1 = strongly disagree,... 5 = strongly agree).

(f) I used a well-organized system of taking lecture notes for this course (1 = strongly disagree,... 5 = strongly agree).

(g) I try to be consistent in my study by keeping up with my courses (1 = strongly disagree,... 5 = strongly agree).

(h) Realistically, how much time outside of class did you give to <u>this</u> course (1 = none; 2 = less than one hour per week; 3 = between 1 and 3 hours per week; 4 = between 3 and 5 hours per week; 5 = more than five hours per week)?

The Cronbach's Alpha of this scale was .82.

9. Class Level (freshman, sophomore, etc.)

<u>Personal Nonacademic Predictors of Student Performance</u>.

10. Age

11. Sex

12. Race

13. Total Family Income (0 = less than $25,000, 1 = $25,000 and above).

14. Personal Problems was a factor analysis score based on responses to the following two items:

(a) Did anything occur in your life this quarter that interfered with your ability to do well in this course--for example, fraternity/sorority rush, marriage, new job or working hours, sickness in family, financial problems, or personal problems (1 = no; 2 = yes, it interfered with study a little; 3 = yes, it interfered with study greatly)?

(b) I had personal problems which interfered with study this quarter (1 = strongly disagree,... 5 = strongly agree).

Findings

The analysis occurred in two stages. First, in order to provide a basis of comparison with the AID procedure, we examined a multiple regression model predicting SGS. Second, we collapsed predictor variables into categories to use the AID procedure. Categorization of interval level independent variables, while it sacrificed information, was necessary because AID is an analysis of variance technique. On the other hand, analysis of variance is not restricted to a linear assumption and interaction effects add to the variation explained. ACT and SDRT admissions test scores were excluded from the AID procedure due to insufficient cases.[6]

Multiple Regression Analysis

Table 1 presents SGS regressed on predictor variables which were found to have significant zero-order correlations with it. GPA, ACT, and SDRT scores were highly correlated with SGS and with other variables. Thus, these three variables were entered into

Table 1 about here

the regression equation last to avoid obscuring the effects of other predictor variables.[7] Among these other variables, measures of comprehension skills were the strongest predictors of SGS with Class Level and Lack of Personal Problems making significant contributions to explained variation. The admissions test scores and GPA explained an additional 22% of the variation in SGS for a total explained variation of 65%. The variables sex and race were found not to explain any variation in SGS after other variables were controlled.

Automatic Interaction Detection Analysis

The AID procedure involved a series of analysis of variance tests, breaking the sample down according to which student characteristics explained the greatest amount of variation (the largest sum of squares) in SGS. (See Sonquist et al., 1973; OSIRIS III : An Integrated Collection of Computer Programs for the Management and Analysis of Social Science Data, 1973.) The results are presented in the tree diagram of Figure 2. First, the procedure identified the variable explaining the most variation in

Figure 2 about here

SGS and this was GPA. Then it was established which categories of GPA had significantly different mean SGSs, and significant differences were found between high (3.0 to 4.0), moderately high (2.5 to 3.0), moderately low (1.5 to 2.5) and low (0.0 to 1.5) GPA students. Then, each of these GPA categories was treated as a separate subgroup, and the remaining predictor variables were examined to see which explained the greatest amount of variation in SGS in that subgroup. Then subgroups of that predictor variable were examined and the process continued until remaining predictor variables were found to explain less than .8% of the variation in SGS or until the category size diminished to as few as five cases. To better understand how this procedure worked, note that each breakdown, represented by a branch of the tree diagram, resulted in two groups of students who comprised the group to the left. Observing category sizes (n) conveys this. The fact that different variables broke out of the four GPA categories revealed that the relationship of these variables to SGS was different among students of the four categories; that is, statistical interaction was present. (If the same variables had broken out of each GPA subgroup, the model would have been merely additive.) Since the mean of Z scores was zero, the mean SGS for the groups depicted in Figure 2 represented the mean number of standard deviations above (+) or below (-) the course average. The terminal categories, those for which there were no further breakdowns, were numbered in rank order of magnitude. Further, to give substance to the scores, the mean SGS for each category was transformed into an estimate of the proportion of improvement or decline in Letter Grade (LG) associated with each breakdown, with a letter grade defined as 10 course points in accordance with the traditional scale of "A" = 90-100, "B" = 80-90, etc. For example, in the first breakdown, it was observed that having a GPA between 3.0 and 4.0 (A/B+ students) allowed one to predict that on average these students would score 1.2 letter grades above the course mean. The highest scoring category (Category 1) was 12 students who were not only A/B+ students, but also had exceptionally high reading comprehension skills. These skills accounted for an additional .4 LG for an overall group mean 1.6 LGs over the course average.

Notwithstanding the fact that the absence of admissions test scores in the model should have greatly reduced the variation explained in SGS, the AID procedure increased the variation explained to 68% from the 65% explained by the multiple regression model. Thus, the AID model revealed a moderately strong relationship between predictor variables and student performance in the social science course.

A broad look at the tree diagram of Figure 2 was informative in a number of ways. First, high Reading Comprehension was a variable that was significant in three of the four GPA groups, and Course Specific Comprehension was significant in two. Comprehension was a factor in 11 of the 14 terminal groups, 11 categories which comprised about two-thirds of the total sample. This importance of reading comprehension to academic performance corresponds to that of other studies in which reading ability was differentiated from measures of overall academic ability such as entrance exam scores and high-school GPA. For example, Carney and Geis (1981) examined the correlates of first- and fifth- semester GPAs of 490 freshman enrolled in a residential university. Reading ability was significantly correlated with first semester GPA but not with fifth semester GPA. This suggested that the 313 who survived had the threshold level of reading ability needed for academic success, and that environmental factors gain in influence on performance as the educational process proceeds over time. Blustein et al. (1986) investigated the relationship of eight variables to GPA in a population of community college students and found reading comprehension to be one of two significant predictors. Nisbet, Ruble, and Schurr (1982) found that the perception of the ability to read to be related to retention.

The main contribution of this interaction model to understanding was its differentiation of categories of students along highly instructive combinations of variables. The AID procedure was especially effective in centering on the performance of disadvantaged students because the first variable to break out in the analysis was GPA. GPA may be viewed as a proxy of student capability coming into the course, a personal academic variable, and the lower GPA groups may be perceived as disadvantaged compared to the higher GPA groups. Once that breakdown occurred in the analysis, the procedure effectively answered two questions: (1) Is the relationship of student performance to its predictor variables different for various GPA level students (i.e., is there statistical interaction)? (2) If so, can identification of these relationships help determine ways to compensate for academic disadvantage through program interventions?

The asymmetry of the tree diagram in Figure 1 confirms the first question. To answer the second question, Table 2 explores specific subgroups of students more closely. Terminal

Table 2 about here

categories are described and theoretical points are noted. A general observation of the table revealed that standard deviations of SGS were larger for low GPA groups, indicating that some students in these groups made higher grades in the social science course than one would expect given their GPA level going into the course. It was observed also that for category 5 an affinity to course material (perhaps reflecting interest and academic major) and a lack of personal problems helped these C/D+ students to score 0.7 LGs above the course average. Though category 6 students had low GPAs (C/D+) and poor comprehension skills, their ages (23 years and older) were a compensating factor (presumably because of maturity, commitment, and motivation). Category 10 was interesting in that five high GPA students were identified who nonetheless had both general and course specific comprehension problems that adversely affected their grades.

Surprisingly, D/F students who said they used intensive study habits (categories 13 & 14) did less well than their counterparts who claimed to use less intensive ones (category 11). This suggested one of three things: (1) the scale was not highly valid or reliable; (2) intensive study was not sufficient to overcome poor abilities; or (3) these students overrated their study performance. Results of an earlier study by the authors of natural science students lent support to the last explanation: A cluster of F students were found who perceived themselves to be progressing much better than any objective evidence would have suggested. They were grossly disillusioned and confused about the relationship between study process and outcome.

<u>Student Retention Rates Over the 10 Quarter Study Period</u>

The third column of numbers in Table 2 presents the percentage of students in each terminal AID category who met the criteria for having been retained in school. For the total sample, 48.8% of the 206 students were retained in school or were graduated. Since the categories in Table 2 were ranked by mean SGS, and this was highly correlated with GPA, not unexpectedly, retention rates decline with rank. There were a couple of exceptions. First, only one of five students in Category 8 survived. These were older, but poorly equipped, students who did a little better in the social science course than expected. The small sample size precluded explaining this, but perhaps the experience that went with age helped these students in that course but failed them in more technical ones. Second, 71.4% of the students in Category 9, notwithstanding their poorer than expected social science grade, survived in the long run. These B/C+ students with little or no prior knowledge with course material were probably not social science majors or minors. The social science course was perhaps a diversion from an otherwise adequate academic performance. A similar explanation may explain the higher than expected retention rate in Category 7.

While retention rates were marginal overall, this cannot be explained merely by analyzing student performance. Many very capable students dropped out; only two-thirds of the high GPA students remained in school or were graduated. Unfortunately, we were unable to account for this as we did not measure social integration and institutional commitment, variables found to be associated with the voluntary withdrawal of students in good academic standing (Pascarella & Terenzini, 1983; Pascarella, Duby, & Iverson 1983.) One of four (26%) students who had GPAs below 2.0 (C) in the initial quarter survived the study period. Detailed explanations of these variations must await further research. However, the preliminary results lent support to the notion of compensatory interaction effects explained in Bean and Metzner's (1985) model of nontraditional undergraduate student attrition. They suggested that for part-time, older, and commuter students, environmental and academic factors interacted to influence persistence in school. When both factors were favorable (e.g., our Caterories 1 through 5), students remained in school. When environmental factors were unfavorable, persistence declines. Thus, students with moderate academic ability, but personal problems (our Category 8), were more likely to withdraw than their counterparts lacking personal problems (Category 5).

Summary and Conclusion

The hypothesis that a statistical interaction model helps explain student student performance was confirmed. Among high GPA students, personal academic variables--intellectual/conceptual skills, general reading ability, ability to comprehend specific course material, written summarization skills--accounted for a 4 to 11 point increase in mean numerical grade. Personal academic variables accounted for all of the explained variation in SGS among the six terminal groups comprised of A/B+ and B/C+ students (groups 1 - 4, 9, 10 in Figure 2). While these variables were important also for low GPA students, personal problems (nonacademic, social environment factors) were found to be more common and to cause a 4-point mean grade decline. Age was a compensating factor for disadvantaged students; the average score of students 23 years of age and older was 13 points higher than that of younger students. Half of the eight terminal groups among C/D+ and D/F students (groups 5, 6, 8 and 12 in Figure 2) were distinguished by nonacademic variables.

Reading comprehension and course-specific comprehension, an affinity to a specific course, were found to be important factors in student performance. Written summarization skills were also important and prior exposure to related subject matter gave some students an edge. But the performance of disadvantaged students was more likely to be affected by nonacademic factors. The findings suggested also that some disadvantaged students were inclined to assess their situations inaccurately.

It is worthwhile to note which variables failed to predict grade performance. How students evaluated the instructor was not significant, nor were the personal nonacademic factors of sex, race, and family income, once other variables were controlled.

Implications for Program Interventions

The complexities of the educational process demand that two things be considered in structuring program interventions and researching academic outcomes. First, as Kirschenbaum and Perri

(1982) note in a review of studies of academic competence, long-term improvements of any significance require structured, multicomponent interventions. Second, the diversity of factors which influence academic performance results in assorted patterns of student experience. Students with poor reading comprehension and writing skills should be identified, made aware of the implications of their deficiencies, and channelled into remedial courses. Multicomponent interventions might include study skills training and the development of self-regulatory behaviors, actions which would have the most likelihood of improving academic performance (Kirschenbaum & Perri, 1982). Our data suggest that admissions-test scores are good screening devices. Thus, they should be required of all applicants, not merely for admissions assessment, but for requiring probationary remedial coursework.

To avoid course-specific comprehension problems and the adverse effects of lack of prior exposure to subject matter, instructors should be advised to provide overviews of course material. More ambitious instructors might utilize a few of the simple indicators from our questionnaires to identify students with comprehension problems and arrange extra exercises and study sessions.

The obvious need for remedial work among many students in this study suggests that students are not likely to identify their own deficiencies until they have built a poor academic record. This provides a case for requiring deficiency screening and subsequent developmental courses. Academic interventions might be supplemented by vigorous student development using outreach methods to initiate and maintain consistent contact with academic counselors.

We found personal problems to influence student performance and impede persistence toward degree completion. Although many personal nonacademic factors are immutable, their effects on student performance are not. Efforts might be made to assist nontraditional students in coping with academic demands in the face of personal role conflicts. For example, campus child care services might make the difference for some academically disadvantaged, yet nontraditional, students.

In this study we centered primarily on personal academic traits. Though we did not measure the environmental factors listed in Figure 1, it became apparent that student-directed interventions will succeed only where they are not undermined by unfavorable environmental factors. For the case at hand, and many nontraditional campuses, some alterations in the academic environment are clearly in order. For example, financial aid recipients are required to take a full load of credit courses, but remedial courses are not given for credit. Thus, these courses must be scheduled on top of a regular load. Such restrictions force many disadvantaged students not only to take more coursework than they can handle, or afford financially, but also to remain in courses in which they are failing. Such "catch-22s" must be resolved to more closely fit the realities of commuter campuses with open admissions policies. Further research on academic performance should involve multicampus comparisons so that more of the variables in Figure 1 may be directly measured.

Though our sample was one of convenience, the data allowed at least a preliminary focus on interaction effects. The utility of a statistical interaction model hopefully will encourage others to replicate their research with the primary aim of detecting compensatory effects.

References

Bailey, K. D. (1978). Methods of social research. New York: The Free Press.

Bean, J. P., & Metzner, B. S. (1985). A conceptual model of nontraditional undergraduate student attrition. Review of Educational Research, 55, 485-540.

Blalock, H. M., Jr. (1979). Social statistics (rev. 2nd ed.). New York: McGraw-Hill.

Blustein, D. L., Judd, T. P., Krom, J., Vinlar, B., Padilla, E., Wedemeyer, R., & Williams, D. (1986). Identifying predictors of academic performance of community college students. Journal of College Student Personnel, 27, 242-249.

Boyer, E. L. (1984). High school: A report on secondary education in America. New York: Harper & Row.

Carney, M. & Geis, L. (1981). Reading ability, academic performance, and college attrition. Journal of College Student Personnel, 22, 55-59.

Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. Psychometrika, 16, 297-334.

Eagle, N. (1982). An attempt to optimize the early identification of the potential dropout: Use of dynamic predictors, differentiated criterion groups, and alternative discriminant function methodology. Paper presented at the Annual Forum of the Association for Institutional Research, Denver. (ERIC Document Reproduction Service No. ED 221 150)

Erickson, L., Kimmel, E. W., Murphy, M. T. & Newcomer, W. J. (1976). Back to school--The older-than-average student. College and University, 51, 679-692.

Fox, R. N. (1986). Application of a conceptual model of college withdrawal to disadvantaged students. American Educational Research Journal, 23, 415-424.

Getzlaf, S. B., Sedlacek, G. M., Kearney, K. A., & Blackwell, J. M. (1984). Two types of voluntary undergraduate attrition: Application of Tinto's model. Research in Higher Education 20, 257-268.

Goldman, R. D., Slaughter, R. E. (1976). Why college grade point average is difficult to predict. Journal of Educational Psychology 68, 9-14.

Greer, L. R. (1980). Persistence and academic success among non-traditional age students at a junior college. Paper presented at the Annual Forum of the Association for Institutional Research, Atlanta. (ERIC Document Reproduction Service No. ED 189 942)

Henry, F. (1982). Multivariate analysis and ordinal data. American Sociological Review, 47, 299-307.

Houston, S., & Schmidt, S. R. (1987). Enhancing classification by combining discriminant analysis with a modified AID procedure. Journal of Experimental Education, 56, 28-35.

Kirschenbaum, D. S., & Perri, M. G. (1982). Improving academic competence in adults: A review of recent research. Journal of Counseling Psychology, 29, 76-94.

Kulik, C. C., Kulik, J. A., & Shwalb, B. J. (1983). College programs for high-risk and disadvantaged students: A meta-analysis of findings. Review of Educational Research 53, 397-414.

Likert, R. (1932). A technique for the measurement of attitudes. Archives of Psychology, 21, 140.

National Commission on Excellence in Education. (1983). A nation at risk: The imperative for educational reform. Washington, DC: U.S. Government Printing Office.

Nisbet, J., Ruble, V. E., & Schurr, K. T. (1982). Predictors of academic success with high risk college students. Journal of College Student Personnel, 23, 227-235.

O'Brien, R. M. (1979). The use of Pearson's r with ordinal data. American Sociological Review, 44, 851-857.

OSIRIS III: An integrated collection of computer programs for the management and analysis of social science data. (1973). Ann Arbor: University of Michigan, Institute of Social Research.

Ott, L., Larson, R.F., & Mendenhall, W. (1983). Statistics: A tool for the social sciences (3rd ed.). Boston: Duxbury Press.

Pascarella, E. T., Duby, P. B., & Iverson, B. K. (1983). A test and reconceptualization of a theoretical model of college withdrawal in a commuter institution setting. Sociology of Education, 56, 88-100.

Pascarella, E. T., Duby, P. B., Miller, V. A., & Rasher, S. P. (1981). Preenrollment variables and academic performance as predictors of freshman year persistence, early withdrawal, and stopout behavior in an urban, nonresidential university. Research in Higher Education, 15, 329-349.

Pascarella, E. T., Smart, J. C., & Ethington, C. A. (1986). Long-term persistence of two-year college students. Research in Higher Education, 24, 47-71.

Pascarella, E. T., & Terenzini, P. T. (1980). Predicting freshman persistence and voluntary dropout decisions from a theoretical model. Journal of Higher Education, 51, 60-75.

Pascarella, E. T., & Terenzini, P. T. (1983). Predicting voluntary freshman year persistence/withdrawal behavior in a residential university: A path analytic validation of Tinto's Model. Journal of Educational Psychology, 75, 215-226.

Peng, S. S., & Fetters, W. B. (1978). Variables involved in withdrawal during the first two years of college: Preliminary findings from the national longitudinal study of the high school class of 1972. American Educational Research Journal 15, 361-372.

Rovezzi-Carroll, S., & Thompson, D. L. (1980). Forecasting college success for low-income students. Journal of College Student Personnel, 21, 340-343.

Sonquist, J. A., Baker, E. L., & Morgan, J. N. (1973). Searching for structure. Ann Arbor: University of Michigan, Institute of Social Research.

Staman, E. M. (1980). Predicting student attrition at an urban college. Dissertation Abstracts International, 40, 4440A. (University Microfilms No. 80-02,565)

Taylor, W. (1953). Cloze procedure: a new tool for measuring readability. Journalism Quarterly, 30, 414-438.

Tinto, V. (1975). Dropout from higher education: A theoretical synthesis of recent research. Review of Educational Research 45, 89-125.

Footnotes

[1] In much of the literature, many of the personal factors listed in Figure 1 are termed pre-enrollment predictors, while environmental and educational process variables are termed post-enrollment predictors (Pascarella & Terenzini, 1980; Pascarella, Duby, Miller, & Rasher, 1981; Pascarella, Smart, & Ethington, 1986).

[2] Statistical interaction involves multiplicative in addition to additive effects for two or more independent (predictor) variables on a dependent (outcome) variable. For example, if the dependent variable was income, and race and sex were independent variables, statistical interaction would be present if black women were found to have even lower incomes than would be expected by their being black and female. In other words, one would not merely add the effects of sex and race, but add additional effects due to the "peculiar" combination, black-female. Black females suffer a double dose of discrimination or a multiplicative effect. Put another way, the relationship of sex to income differs for males and females (Blalock, 1979, pp. 355-366).

[3] For example, a student who made a 78 in the sociology course would have made an 85 in the political science course because the instructor in the latter was more lenient in his grading and the

average of his course was higher. Prior to standardizing the grade scores, the best predictor of course grade was the subject a student was taking. After standardizing, course subject did not account for any of the variation in course grade. Treating course grade relative to the average is clearly the meaningful way to do it.

[4]Only 36.6% of the sample had GPAs fluctuating by 1.5 between their highest and lowest quarters over the study period.

[5]Variables 6, 8, and 14 were constructed from questionnaire items with Likert (1932) response categories (strongly agree, scored 5, to strongly disagree, scored 1). Then, zero-order correlations were computed and items that correlated .4 or above with other items were formulated into weighted composite scales based on Factor Analysis (Bailey, 1978, pp. 365-370). The internal consistency of a scale was assessed with Cronbach's Alpha reliability coefficient (Cronbach, 1951). Prior to conducting factor analysis which assumes interval-level data, each item was examined to see if it were feasible to treat these ordinal (ranked) response categories as interval data. Questionnaire items that had significantly skewed responses were eliminated. Ordinal scales have been found to give the same statistical outcomes as interval scales with "robust" statistics such as

Pearson's r and analysis of variance (O'Brien, 1979; Henry, 1982).

[6]Only 129 and 96 students took the ACT and Stanford Diagnostic Reading Test (SDRT), respectively. The regression coefficients for these variables with others were based, then, on only part of the sample. Since those without these test scores were primarily transfer students who tend to be better students because they have survived other programs, the coefficients are probably underestimated and, thus, conservative.

[7]If a forward stepwise regression were computed where variables entered the equation according to the magnitude of their correlation with Standardized Grade Score (SGS), GPA, ACT, and SDRT scores would have entered the equation first. Other predictor variables, because they are highly correlated with these three, would then have failed to explain additional variation (sums of squares) in SGS beyond that explained by these variables. We did not want this to occur because GPA, ACT, and SDRT are not directly interpretable as are the other variables. Thus, they were held out of the equation until the other variables were included.

Table 1

Standardized Grade Scores Regressed on Selected Student Characteristics With Admissions-Test Scores and Grade Point Average (GPA) Entered Last

Independent V riables	R	R^2	R^2 Change	r	Beta
(1) ALL BUT ADMISSIONS TESTS,GPA					
Course-Specific Comprehension	.37	.13	.13***	.37***	.11
Reading Comprehension	.49	.24	.11***	.34***	.13
Written Summarization Skills	.53	.29	.05***	.32***	-.01
Class Level	.57	.33	.04***	.22**	.30**
Lack of Personal Problems	.61	.38	.05***	.27***	.20*
Causal Inference Ability	.64	.40	.02***	.26***	-.04
Age	.65	.42	.02***	.19**	.12
Prior Knowledge of Course Material	.66	.43	.01*	.18**	-.07
TOTAL R^2 for (1)	.43***				
(2) ADMISSION TESTS AND GPA					
ACT Score[a]	.76	.58	.15***	.58***	.36**
Intensive Study Habits[b]	.78	.60	.02***	-.05	.14
Stanford Diagnostic Test[c]	.80	.64	.04***	.55***	.30*
GPA	.81	.65	.01*	.63***	.15
TOTAL R^2 for (2)	.22***				
TOTAL R^2 FOR ALL VARIABLES	.65***				

[a]ACT coefficients computed for 129 available cases. [b]Intensive Study Habits entered the equation late because its effects were suppressed until ACT entered. [c]Stanford Diagnostic Test Scores coefficients computed for 96 available cases.

* $p<.05$, one-tailed. ** $p<.01$, one-tailed. *** $p<.001$, one-tailed.

Table 2

Ranked Mean Standardized Grade Scores for Student Categories from AID, and Retention Rates

Student category	Mean		RR[a]	n	Gain or loss in letter grade	Grade rec'd	Notes on compensatory effects
(1) A/B+, very high reading comprehension	1.32	.49	67%	12	1.6	A	
(2) A/B+, not extremely high reading comprehension but mod. to good written summary skills	1.10	.50	67	15	1.3	A/B	
(3) A/B+, not extremely high reading comprehension, poor written summary skills, but few course-specific comprehension problems	.86	.43	78	9	1.0	B	Affinity to course material compensated for moderate academic abilities
(4) B/C+, moderate to high prior knowledge of course	.66	.61	58	24	.8	B/C	
(5) C/D+, encountered few course-specific comprehension problems, no personal problems	.56	.42	50	14	.7	B/C	Better than expected due to affinity to course & no personal problems
(6) C/D+, encountered course-specific comprehension problems, mod. to very poor reading skills, 23 years & older	.30	.52	20	5	.4	C+	Being older helped
(7) C/D+, encountered course-specific comprehension problems, had mod. to good reading comprehension skills, 23 years & older	-.01	.46	50	17	.0	C	Slightly better than expected; reading comprehension compensated for course-specific problems

(Continued)

Table 2. Continued

(8) C/D+, encountered few course-specific comprehension problems, but had personal problems	-.04	.56	36	14	-.1	C	Better than expected due to affinity to course material
(9) B/C+, little or no prior knowledge of course	-.09	.64	71	26	-.1	C	Slightly worse than expected due to lack of prior exposure
(10) A/B+, not extremely high reading comprehension skills, poor written summary skills, encountered course-specific comprehension problems	-.15	.54	40	5	-.2	C/D+	Did much worse than expected from GPA, but not than predicted from other variables
(11) D/F, less intensive study habits	-.75	.59	21	19	-.9	D	
(12) C/D+, encountered course-specific comprehension problems, had mod. to very poor reading comprehension skills, young (17-22 years old)	-.89	.64	43	34	-1.1	D-	Did worse than expected due to both course-specific & reading comprehension problems
(13) D/F, very intensive study habits, average to mod. high reading comprehension skills	-1.11	.97	00	7	-1.3	D-/F	Reading skills helped some.
(14) D/F, very intensive study habits, poor reading comprehension skills	-1.87	.85	00	5	-2.2	F	Intensive study either overrated by student or did not help
ALL STUDENTS	0.00	.96	49	206	0.0	C	

[a]RR = Retention Rate = % of category remaining in school in the study period or being graduated.

Figure Captions

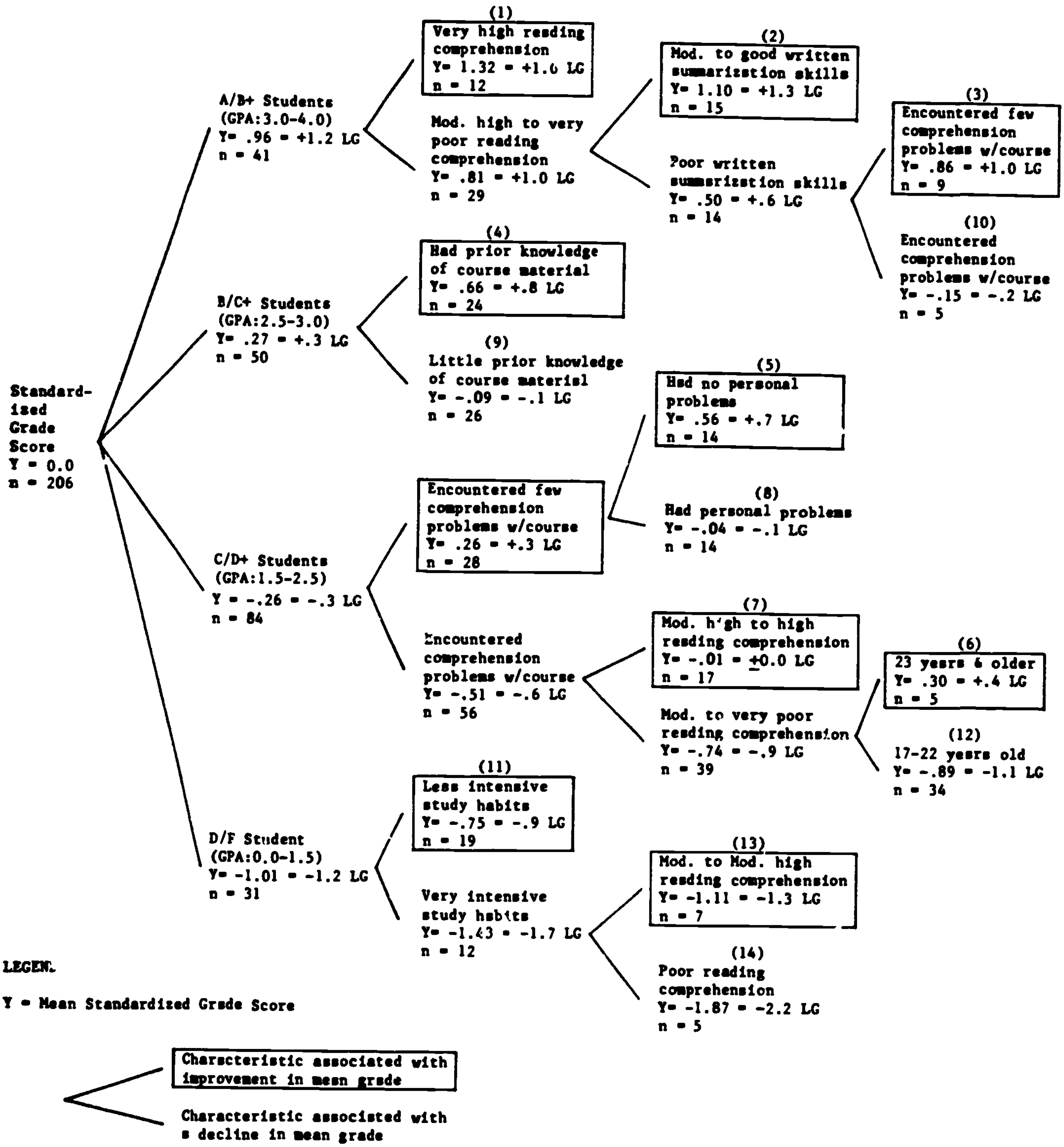
Figure 1. Types of variables hypothesized in the literature to affect academic performance and student retention

Figure 2. Means of Standardized Grade Scores for categories derived with Automatic Interaction Detection: 206 students in introductory social science courses

Figure 1.

	Personal (Internal)	Environmental (External)
Academic	EDUCATIONAL BACKGROUND: High school GPA High school curriculum COMPETENCIES: Reading comprehension Writing & math skills EDUCATIONAL GOALS: Vocational interest Academic commitment BEHAVIORAL FACTORS: Study behavior Academic adjustment College GPA	TYPE OF CAMPUS: Traditional vs. non-traditional/commuter Community college vs. 4-year teaching college vs. research university Size of student body EDUCATIONAL ENVIRONMENT: Intensity & duration of faculty-student interaction Quality of facilities Class size Remedial, guidance & support services
Nonacademic	DEMOGRAPHIC FACTORS: Age, sex, race, ethnicity, socioeconomic status PERSONALITY FACTORS: Self-concept Self-esteem Self-control ROLE CONFLICTS: Interpersonal & financial stability Employment status Full-time vs. part-time status ROLE ADJUSTMENT: Student social integration	TYPE OF CAMPUS STUDENT ENVIRONMENT: Interaction with peers, student subculture AVAILABILITY OF CAMPUS STUDENT ACTIVITIES: Extracurricular programs STUDENT GROUPS/ ASSOCIATIONS

Figure 2.



± LG = Estimated improvement (+) or decline (-) in mean letter grade compared to total sample.

( ) = Terminal categories numbered in rank order of mean standardized grade score.