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Predicting Retention in Online General Education Courses

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A classification rule was developed to predict undergraduate students' withdrawal from or completion of fully online general education courses. A multivariate technique, predictive discriminant analysis (PDA), was used. High school grade point average and SAT mathematics score were shown to be related to retention in the online university courses. Locus of control and financial aid were able to identify dropout and completion with 74.5% accuracy.

Variables and factors that could influence student dropout and persistence in online distance education have been identified by several studies (Ehrman 1990; Kemp 2002; Parker 1999; Whittington 1995). These studies investigated the relationship between persistence and demographic characteristics such as educational background, age, and gender in distance learning.

Diaz (2002) found successful online students exhibit a higher grade point average (GPA) prior to enrollment in an online course than unsuccessful students. He found that online students are generally older, have completed more college credit hours and more degree programs, and have a higher all-college prior GPA than their traditional counterparts. According to Carr (2000), age may be related to low course completion and poor retention rates in distance education courses. Nesler (1999) found that retention in an online liberal arts program was influenced by demographic characteristics such as gender and educational background. Kember (1989) developed a longitudinal model of dropout from distance education that in-

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cluded the components of student background characteristics and academic and social integration.

Utilizing discriminant analysis, Parker (1999) found locus of control and source of financial assistance were able to predict dropout rate with an accuracy of 85%. Fjortoft (1995) identified intrinsic motivation as the significant factor in predicting 23% of variance in retention in distance education along with the variables of age and level of student. Dille and Mezack (1991) showed that successful students had more internal motivation, whereas unsuccessful students tended to have external motivation. Liu, Lavelle, and Andris (2002), using a pretest and posttest design, found an increase in student internal locus of control at the completion of an online course.

College Retention Literature

The foundational work for college-level retention was that done by Tinto (1975). In his "Theory of Student Departure," Tinto proposed a retention model conceptualizing student persistence influenced by a student's pre-entry attributes, goals and commitments, academic, and social integration. Andreu (2002), using Tinto's model, selected and defined more than twenty variables.

In a study by Snyder et al. (2002), logistic regression was utilized to examine the academic success and retention of first-year college students. High school GPA was a strong predictor for completing courses and being retained in college. Murtaugh, Burns, and Schuster (1999) found college attrition increased with age and decreased with increasing high school GPA and first-quarter GPA.

The literature on retention (staying in college) is more fully developed than the research on completing or withdrawing from college courses. However, in one study, Ahmadi and Raiszadeh (1990), using ethnicity, gender, SAT scores (see http://www.collegeboard.com/testing/), and GPA, were able to predict completion and noncompletion with a 72.74% accuracy (using a two-group predictive discriminant analysis) in an introductory business statistics course.

This study is important in that it seeks to identify student characteristics related to completion and noncompletion in the online learning environment. This study examines students enrolled in fully online, lower division, undergraduate courses offered by the University System of Georgia. System records indicate that over a five-semester period, approximately 30% of enrolled students dropped a course by the end of the semester. Various studies (Lorenzetti 2002) report dropout rates as high as 50% from distance education classes. Further investigations of predicting students' persistence (i.e., completion and withdrawal) in an online environment based on significant variables (e.g., demographic, educational factors, and locus of control) derived from the previous conceptual literature are necessary.

Research Questions

This research investigated the classification of students in online courses into completion and withdrawal categories using selected independent variables. In essence, the research sought to determine the accuracy of group membership based on the "predictor" variables.

The following research questions were examined:

1. How accurately can a student's persistence (i.e., group membership of completion or withdrawal) be predicted in online learning courses?
2. Which predictors are the most important with respect to predictive accuracy of a student's group membership (completion and withdrawal)?
3. Can a prediction/classification rule be developed that may be used with a "new" analysis unit (e.g., students)?

Research Design

Study Population

The participants in this study were students across five semesters who enrolled in eCore® courses—electronically delivered, undergraduate core courses taught using WebCT. eCore® courses were collaboratively developed by University System of Georgia faculty and instructional design teams and the courses are offered fully online by six affiliate university system institutions. Included are general education courses in the humanities, science, and social sciences.

Predictive Discriminant Analysis

Increasingly, researchers utilize discriminant analysis in empirical studies of higher education and distance education (Kemp 2002; Parker 1999). In the social and behavioral sciences, discriminant analysis has been applied to serve research purposes such as (1) developing a rule to predict group membership using a set of predictor variables—that is, classifying analysis of units (e.g., students) into groups (predictive discriminant analysis [PDA]); and (2) describing group differences (descriptive discriminant analysis [DDA]) (Fan and Wang 1999; Huberty 1994).

Multivariate analysis of variance (MANOVA) is used to assess the effects of grouping variables on a set of outcome variables. For example, researchers may be interested in understanding if there are statistical group differences (e.g., students' ethnic backgrounds) on their SAT verbal and mathematics scores. Conducting MANOVA before PDA is often seen; however, this study did not make such an attempt because other studies have indicated the problems of reporting both PDA and DDA and MANOVA results in the PDA study (Huberty and Hussein 2003).

Keselman et al. (1998) indicated that a reason for including both PDA and DDA and MANOVA results is simply that some computer programs provide both information (of PDA and DDA and MANOVA), and the analyses are not done for the purposes of the study. On the other hand, Huberty (1994) recommended that researchers first conduct MANOVA, if significant group differences are found, then DDA is used to describe the difference between grouping variables and the outcome variables; that is, DDA is used to interpret the difference found using MANOVA. A choice between PDA and DDA should be based on the research questions.

Research has shown that both PDA and logistic regression approaches are efficient for predicting group membership. In this study, PDA is used because it has several advantages over logistic regression. First, PDA provides a way of detecting outliers using typicality probability and posterior probability. Second, PDA is able to consider the prior information. For example, previous information about the dropout rate can certainly be included in the analyses. Third, PDA is able to classify new analysis units (e.g., students) with a well-developed prediction rule. Finally, both PDA and logistic regression performed comparably in the binary group membership when the two groups have equal covariance matrix (Fan and Wang 1999).

The purpose of this study was to develop a rule for predicting group membership of students in distance education courses. Thus, a two-group PDA was used to predict student dropout or completion of distance learning courses. Two statistical analysis programs, SPSS (ver. 11.0) and SAS (ver. 6.12), were utilized to conduct the data analysis in this study.

Variable Descriptions and Selection

In a meaningful PDA study, the predictor variables and grouping variable must be well defined. In this study, the grouping variable was labeled as completers and noncompleters. Two groups of students were thus classified as (1) students who successfully completed a specific course during the semester, and (2) students who withdrew from a specific course during the semester.

The nine predictor variables used in this study are shown in Table 1. Two subsets of predictor variables were derived from the previous empirical research and conceptual literature on distance education. These two subsets were used to predict student completion and withdrawal in the online learning context using PDA. Subset A included seven predictor variables focusing on students' demographic and academic information, such as gender,[1] age, verbal ability, mathematic ability, current credit hours, high school achievement (GPA), and college achievement (GPA) (Diaz 2002; Ehrman 1990; Nesler 1999; Whittington 1995). Two predictor variables, locus of control and financial aid, were used for analyses in subset B of this research (Dille and Mezack 1991; Fjortoft 1995; Liu, Lavelle, and Andris 2002; Parker 1999). This decision to create subsets was based on research by Huberty and Lowman (1998), who suggest that a subset of predictors[2] may be created if the subset makes substantive sense and is based on previous research findings.

Instrumentation

Rotter's (1966) Internal–External locus of control scale (I–E scale) was used in this study because previous research (Dille and Mezack 1991; Liu, Lavelle, and Andris 2002; Parker 1999) found that locus of control measured by Rotter's I–E scale was significantly related to persistence in distance learning. Rotter's I–E scale is a forced-choice, twenty-nine-item scale (with six items designed as filler) that determines a person's perception of motiva-

Table 1. Predictor Variables for Predictive Discriminant Analysis

Predictor Variable	Indicators	Measures
1. Gender	Female, male	0, 1
2. Age	Number of years	18–54
3. Verbal ability	SAT verbal score	200–800
4. Math ability	SAT math score	200–800
5. Current credit hours	Hours attempted	3–23
6. HS GPA	High school GPA	0–4.00
7. College GPA	College GPA	0–4.00
8. Financial aid	No, yes	0, 1
9. Locus of control	Rotter's I-E score	0–23

Note. Predictors 1 to 7 are used in subset A and predictors 8 and 9 are used in subset B.

tion. Lower scores indicate internal locus of control, while higher scores reflect external locus of control. Rotter scores range from one to twenty-three.

Locus of control indicates the difference between internal and external motivation. Individuals with internal motivation believe that events occurred due to their own interest, needs, and behavior. Those with external motivation believe that events are decided by environmental factors such as rewards and punishment.

For each item, respondents were given two statements (a and b), and they were asked to select the item with which they most strongly agreed. For example, one pair stated, (a) "Many of the unhappy things in people's lives are partly due to bad luck" and (b) "People's misfortunes result from the mistakes they make." Another pair said, (a) "The idea that teachers are unfair to students is nonsense" and (b) "Most students don't realize the extent to which their grades are influenced by accidental happenings."

The internal consistency and test–retest reliability of the test were quite stable across different samples (Rotter 1966, 13). Strong evidence of construct and discriminant validity was also provided in Rotter's reporting on the instrument.

Participants and Procedure

The participants were students who enrolled in eCore® courses at the University System of Georgia in spring 2002. The original data matrix had 389 cases (i.e., students). In preparing the data for analysis, 146 cases were deleted due to multiple enrollments. For example, if a student enrolled in more than one course (e.g., English and mathematics), only one case was retained. This procedure eliminated duplicate rows of demographic and academic information. Using the definition of the grouping variable (i.e., one must be a completer or noncompleter), an additional thirty-two cases were eliminated due to membership in both groups (completion or noncompletion). Thus, 211 students were assigned to two well-defined groups.

Near the beginning of the semester, students were asked to complete Rotter's I–E scale and were informed of their rights as research participants. Students were free to decline participation or they could withdraw their participation at any time. If they agreed to participate in the study, they were provided sufficient time to complete the Rotter survey. Approval to conduct the study was granted by the University's Office of Human Subjects.

As noted previously, the foundation for the initial choice of two subsets of predictors was based on earlier research and theory. Thus, two samples were obtained for analyzing the two subsets of PDA. For subset A (see variables in Table 1), student demographic and academic information were collected from existing student records. A total of 78 of 211 (37%) students were used to conduct the PDA after the listwise deletion. Listwise deletion excluded the cases with missing values on any required predictor variables. For example, if a student had one missing predictor variable (e.g., verbal ability) from the total of seven predictor variables, then the student was excluded from the data matrix due to the listwise deletion.

The subset A sample was composed primarily of females (75%). The majority of participants identified themselves as White (79.9%), 14.4% defined themselves as African American, 2.9% as multiracial, 1.4% as Hispanic, 1% as Asian Pacific Islander, and 0.5% as American Indian. The average age was 26.96 years (*SD* = 7.90).

For subset B, an online survey of student information and Rotter's (I–E) Locus of Control instrument was used to determine a student's perception of motivation and the availability of financial aid. A total of 51 of 211 (24%) students were used to conduct subset B PDA after the listwise deletion. Female comprised 84.3% of the subset B sample. The percentage of White students was 76.5%, African American 19.5%, multiracial 2%, Hispanic 2%, Asian Pacific Islander 0%, and American Indian 0%. Among the students, 78.4% received financial aid. The average age was 31.80 years (*SD* = 8.85).

Results

PDA Results for Subset A

Table 2 presents the means and standard deviations for seven predictor variables of two classified groups (e.g., completer and noncompleter). The results of error correlations for seven predictor variables are given in Table 3. It is not surprising that there was a significant and positive relation between SAT math and verbal scores ($r = 0.47$). High school GPA also had a positive and significant relation with college GPA ($r = 0.22$) and SAT math scores ($r = 0.23$).

As in most analysis situations, it is imperative to examine the data conditions before conducting a PDA study. In addition, the decision of which form of the classification rule (linear or quadratic) to apply is based on two data conditions, normality[3] and covariance structure.[4] The results showed there were no significantly nonnormally distributed variables, because both skewness and kurtosis values for all variables were within the normality criteria ($|\ 2.0\ |$). The data appeared to be fairly univariately and multivariately normally distributed. For this study, a linear classification

Table 2. Means and Standard Deviation for Seven Predictor Variables in Each Group (N = 78)

	Completers (n = 59)		Noncompleters (n = 19)	
Variable	***M***	***SD***	***M***	***SD***
1. Gender	0.15	0.37	0.15	0.36
2. Age	27.21	7.83	26.88	7.98
3. SAT-Verbal	495.79	73.20	511.19	85.34
4. SAT-Math	481.58	88.71	477.97	77.65
5. Current credit hours	10.84	4.34	9.29	5.07
6. HS GPA	2.68	0.47	2.95	0.58
7. College GPA	2.42	0.69	2.60	0.76

Note: 75% defined themselves as females, and 25% defined themselves as males.

Table 3. Error Correlations for Seven Predictor Variables

Variable	1	2	3	4	5	6	7
1. Gender	1.000						
2. Age	0.057	1.000					
3. SAT-Verbal	0.075	–0.178	1.000				
4. SAT-Math	0.069	–0.187	0.468*	1.000			
5. Current credit hours	–0.126	–0.184	–0.026	–0.048	1.000		
6. HS GPA	–0.263	–0.213	0.116	0.232*	0.233*	1.000	
7. College GPA	–0.079	0.222	0.192	0.194	0.140	0.217	1.000

*$p < .05$.

rule is employed because the population covariance matrices in the two groups are nearly equal. The result of Box's M test yields a large p value (Box's M = 35.22; F = 1.07; p = . 373).

The particular interest of this study is to determine how well a student can be correctly classified into dropout and completion based on his or her scores on the seven predictors. Huberty (1994) recommends that the external Leave-One-Out (L-O-O)[5] estimate is a better estimator for hit rates than the internal estimate; consequently, the results of linear external L-O-O classification hit rates are reported in Table 4. As can be seen in this table, a two-group PDA was able to classify student dropout with an accuracy of 52.6% and completion with 66.1%. The overall hit rate was 62.8%.

Standardized test statistics and effect size index (improvement over chance descriptive statistic) were computed to assess the effectiveness of

Table 4. Linear External Leave-One-Out Classification Results for Subset A

Actual Group Membership	Predicted Group Membership		
	Dropout	**Completer**	**Total**
Dropout	10 (52.6%)	9 (47.4%)	19
Completer	20 (33.9%)	39 (66.1%)	59
Total	30	48	78

Note: 62.8% of cross-validated grouped cases were correctly classified.

the classification (Huberty 1994, 127). The results of test statistics show that the actual classification results are better than chance ($z = 2.26$; $p < .05$). The effect size index revealed that about 26% fewer misclassifications were made by using a linear classification rule than if classifications were done by chance.

It is also informative to ask the question: Which predictors are the most important with respect to contribution to predictive power of accuracy? In other words, the purpose of conducting a PDA study is to assess the relative importance of a set of predictor variables; consequently, predictor variables may be ranked in terms of contribution to the respective group hit rate or the total-group hit rate.

Table 5 shows the results of total group L-O-O hit rates for seven-variable analyses (ordered). By using seven "six predictor" analyses (leave one variable out each time), we may conclude that high school GPA and SAT math score are the most important predictors because their L-O-O hit rate decreased the most. Therefore, high school GPA and SAT math score are considered to be the most important predictors in the study of subset A.

Table 5. Hit Rates and Variable Ranks

Variable Deleted	Leave-One-Out Total Group Hit Rate	Rank
High school GPA	0.484	1
SAT-Math	0.564	2
Current credit hours	0.577	3
College GPA	0.635	4
Age	0.641	6
Gender	0.641	6
SAT-Verbal	0.641	6

PDA Results for Subset B

Table 6 presents the means, standard deviations, and error correlations for the predictor variables in subset B. The results of linear external L-O-O classification hit rates are reported in Table 7, which indicates that 60% of student dropout and 76.1% of student completion were correctly classified. Overall hit rate was 74.5%.

The results of test statistics indicated that the actual classification results do better than chance ($z = 3.50$; $p < .05$). The effect size index suggested about 49% fewer misclassifications would be made by using a linear classification rule than if classification were done by chance alone.

Application of PDA Rule: Classifying New Students

One practical feature of conducting a PDA study is to utilize the prediction information for student advisement purposes. However, researchers have rarely discussed this applied approach in the PDA context. This approach involved developing a classification rule with new students in this study. For example, if a two-group PDA were able to provide some rational prediction,

Table 6. Means, Standard Deviation, and Error Correlations for Two Predictor Variables in Subset B (*N* = 51)

	Completers (*n* = 46)		Noncompleters (*n* = 5)		Error Correlations	
Variable	***M***	***SD***	***M***	***SD***	**Financial Aid**	**Rotter Score**
1. Financial aid	0.83	0.38	0.40	0.55	1.00	—
2. Rotter score	8.98	3.55	6.00	2.35	0.02	1.00

Table 7. Linear External Leave-One-Out Classification Results for Subset B

	Predicted Group Membership		
Actual Group Membership	**Dropout**	**Completer**	**Total**
Dropout	3 (60%)	2 (40%)	5
Completer	11 (23.9%)	35 (76.1%)	46
Total	14	37	51

Note: 74.5% of cross-validated grouped cases were correctly classified.

such as in subset B for eCore® students in Georgia, it is also informative to assess predictive accuracy by applying subset B to another sample (e.g., using data from students in a different online program or context).

Heuristic data with five new students' information about availability of financial aid and the Rotter's scores are provided in Table 8. According to Huberty and Lowman (1998), a student is assigned to the group based on the largest posterior probability value and linear classification function (LCF)[6] score. Therefore, we were able to classify Students 1, 2, 3 and 5 into a completion group and Student 4 into the noncompletion (i.e., dropout) group (see Table 8).

On a practical level, this information could be used by advisors to identify students who are at risk for attrition or for whom more information about course requirements, expectations, and activities could be beneficial. The data could also be used to build models of intervention for students who are at risk or are considering dropping an online course. Although the PDA model cannot predict with 100% accuracy, it should be useful in identifying and supporting successful course completion for the maximum number of students. Parker (1999) also suggested that the identification of a consistent set of persistence variables might assist counselors and faculty in placing students in appropriate educational settings, and thus increase retention.

Conclusions and Limitations

This study contributes to the literature by investigating the ability to predict student persistence (i.e., completion and withdrawal) in an online environment by developing a classification rule. For subset A (students' demographic and academic information), a two-group PDA was able to predict students' completion and withdrawal with an accuracy of 62.8%. By using all but one predictor analysis, high school achievement (high school GPA)

Table 8. Five New Students' Information and Classified Group Membership

Student	Financial Aid	Rotter Score	Withdrawer	Completer
1	1	4	PP_1 = .495	PP_2 = **.505**
2	1	5	PP_1 = .428	PP_2 = **.572**
3	1	6	PP_1 = .363	PP_2 = **.637**
4	0	11	PP_1 = **.667**	PP_2 = .333
5	0	15	PP_1 = .402	PP_2 = **.598**

Note: Bold value is the largest posterior probability value.

and mathematic ability were found to be the most important predictors in subset A. This supports Diaz's (2002) finding that successful online students exhibited a higher GPA prior to enrollment in the online course than unsuccessful students. The prediction rule in subset B (locus of control and availability of financial assistance) was able to predict students' group membership with 74.5% accuracy. Similar to Parker's (1999) findings, these two variables were considered to be significant predictors. In addition, this study has identified significant predictors related to retention in online education and confirms findings from earlier studies (Ehrman 1990; Kemp 2002; Parker 1999; Whittington 1995).

There are several limitations of this study. First, the sample size might affect the stability of the classification rule, which is important in the PDA approach; the results of this study must be interpreted with caution due to the lack of large sample size. As noted, the prediction rule developed in this study may be tested on another available sample. In addition, comparisons of these classification results may provide critical information with respect to the stability of the prediction rule. Second, the nature of our data set did not allow for predicting retention for male students due to their relative small proportion in the samples. Replication of this topic with a larger sample size and another sample is needed to ensure rational prediction. Further investigation of the relationship between academic achievement, locus of control, and motivation in distance education is required for gaining insight into persistence and attrition in an online learning environment.

Notes

1. According to Huberty and Lowman (1998), some categorical predictors would certainly be included in the PDA predictor selection (see Table 1).
2. Although the stepwise analysis approach has been applied in many studies, this approach also has been criticized by some researchers. An all possible subsets approach is suggested by Huberty (1994, 122–126).
3. Normality evaluation was checked by examining descriptive measures of skewness and kurtosis and normal probability plots.
4. Another data condition to check is the equality of the k group covariance matrices. If the k group covariance matrices are nearly equal, linear classification functions (LCFs) would be reported; however, if the k covariance matrices are not equal, quadratic classification functions (QCFs) would be suggested in a PDA. Box's M test is a test of equality of the population covariance matrices. The null hypothesis assumes that the population covariance matrices are equal. A discussion of linear versus quadratic composites in PDA is reviewed by Huberty (1994, 58–61).
5. In PDA context, an external Leave-One-Out (L-O-O) analysis is necessary to obtain an unbiased estimate while internal analysis is to obtain biased estimate. This is analogous

to multiple regression scenarios where adjusted R^2 is unbiased estimate while R^2 is biased estimate (Huberty 1994).

6. More illustrations for posterior probabilities (PP) and linear classification function (LCF) are discussed by Huberty (1994).

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