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ABSTRACT

This report attempts to profile students who participated in a computer-assisted language learning (CALL) research and development project. The researchers hoped to find some pattern or common denominator within each group i.e., the successes, the failures, and the dropouts, that would identify group membership and distinguish one group from another in order to further understand the characteristics of language learners and to be in a position to rationally design alternative methods of computer-assisted language learning for failures and dropouts. To accomplish this objective, three groups of factors were examined, namely, individual characteristics, strategy use, and course information, to try to account for students' differential performance. The subjects for the study were 158 students enrolled in freshman composition classes during the spring semester, 1990, at Northern Arizona University in Flagstaff. Participants undertook four CALL computerized reading and note-taking lessons; two achievement tests were part of each lesson, so that altogether there were eight measures of achievement. After finishing all four lessons, students turned in four types of data from each of the lessons--notes, recall, recognition, and attitude. Scores were then computed for the recall and recognition parts and these scores formed the basis of the grouping criteria. Methods used to assess the three types of factors that might have contributed to group membership are explained next, and finally the Discriminant Function Analysis out of which a profile for the subjects in each group emerged, is discussed. It is concluded that with more information about what students are like; i.e., what kind of profile describes a successful or unsuccessful student, aids can be incorporated into computer assisted lessons that will help students who experience difficulty to overcome their problems rather than leaving them with no alternative but to be forced into the mold of the "ideal" successful student. (KM)

Successes, Failures, and Dropouts in Computer-Assisted Language Lessons

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Introduction

Successes, failures, and dropouts in computer-assisted language learning (CALL) lessons attempts to profile students who participated in a CALL research and development project. It was our hope to find some pattern, some common denominator, within each group--the successes, the failures, and the dropouts--that would identify group membership and distinguish one group from another. If we could do this, we felt we would further our understanding of the characteristics of language learners and would be in a position to rationally design alternative methods of computer-assisted language learning for failures and dropouts.

To accomplish this objective, three groups of factors were examined--individual characteristics, strategies, and course information--to try to account for students' differential performance. In order to establish the setting for our results, first the students who participated in the study will be briefly described. Then, the CALL lessons which were used will be explained. Next, the factors that we thought might contribute to group membership will be explained. Then, the analysis that we used will be described and our results will be presented. Finally, we will discuss our findings.

Subjects

The subjects for this study were students enrolled in freshman composition classes during the Spring semester, 1990, at Northern Arizona University in Flagstaff. A total of 258 students volunteered to do four computerized reading and note-taking lessons (described below). Two achievement tests were part of each lesson, so that all together there were eight measures of achievement. Forty-one students scored above the 70th percentile on all eight different achievement measures; twenty-seven students scored below the 30th percentile on the same eight measures; ninety students dropped out of the project after having agreed to participate. These three groups of students, totalling 158, comprised our successes, failures, and dropouts.

Of the forty-one "successful" students, there were fifteen males and twenty-six females; the median age was nineteen. Of the twenty-seven "failures," eight were male and nineteen were female; the median age was twenty. Among the ninety "dropouts," forty-one were male and forty-nine were female; nineteen was the median age.

Computer Lessons

We designed four computer lessons for our study. Research done by Stahl, Jacobson, Davis and Davis (1989), has shown that prior knowledge, or background knowledge, has an impact on how well the students recall information at a later date. We therefore insured that each of these lessons dealt with a different topic in order to account for the students' schema. These topics were selected from typical readings that college freshmen will have for class, as we thought that the readings should be appropriate for the particular level of our subjects. Although including examples of different types of genres has proven to be beneficial to students (Smith, 1991), we decided to limit our lessons to one genre, that of expository prose. This was to control for the effects that different genres might have on the study. The topics of music appreciation, electric conductivity, minerals, and Aztec civilization were thus chosen.

Although these lessons covered four different topics, they had a uniform method of presentation, based in part on a study by Kiewra and Frank (1986). Each lesson was divided into four parts: a) reading and note-taking, b) recall, c) recognition quiz, and d) attitude questionnaire. Each lesson was done by a student in two consecutive sessions: reading and note-taking (part a) was done during the first session, while the other three parts were done at least one day later during the second session.

The lessons were presented on a VAX computer system and were programmed in Digital's Authoring Language (DAL) and "C." After the student saw the title and directions, he was then presented with the first paragraph of the reading for the reading and note-taking task. In determining the screen display, certain recommendations for programming were followed. First, the student needs to be able to find the "Help" prompt in the same place. Second, paragraphs were kept coherent, not breaking up ideas that naturally need to be viewed together. Finally, the setup was such that no part of the screen overshadowed the content portion, since this is the most important part of the lesson (England, 1989). The screen, then, was divided into three windows: the top window contained one paragraph at a time from the reading; the middle window contained important key words; the third window was an empty space where the student's typed-in notes would appear. When the student completed the reading, he was instructed to quit working and return to the computer lab another day.

The second session began with recall. A subsection of the recall part was the review of notes. In this particular section, the student was shown all the notes that he had prieviously written during the first session. There was no limit as to the time it took for the student to review. After reviewing, the student then went on to type everything he could remember (recall) about the lesson.

After the recall came a recognition quiz. The questions in this section were designed to test the main ideas and important subpoints (generally factual knowledge) of the reading. A multiple choice format with only one correct answer and three foils was used. There were twenty questions.

The last part of this session was the attitude questionnaire which consisted of eleven questions about the student's background knowledge and opinions about the lesson. Based on a Likert scale, a student read a statement and then typed 1 to 5 according to the extent of his agreement or disagreement.

After finishing all four lessons, the student gave us 16 sets of data--notes, recall, recognition, and attitude--four types of data from each of the four lessons. From these, scores were computed for the recall and recognition parts of all four lessons; these scores formed the basis of our grouping criteria. Those whose total scores on all eight measures (four recall and four recognition) were at or above the 70th percentile were placed in the success group. Those whose total scores were at or below the 30th percentile were placed in the failure group. Students who did not do the lessons after having agreed to participate in the study were placed in the dropout group.

The Factors

Three types of factors that might account for group membership of the successes, failures, and dropouts were investigated. These main areas were individual characteristics of the learner, strategy use, and course information. Each of these potential discriminators will be discussed in turn prior to an explanation of the analysis and the description of results.

The first potential factor had to do with individual characteristics of the students in our study. Six different characteristics were of interest. The first few, sex (SEX), age (AGE), first language (LG1), second language (LG2), and the amount of months between high school and college (TMAWAY) were recorded when the students initially agreed to participate in the study. SEX, LG1, LG2, and TMAWAY were treated as dichotomous data.

Finally, we had the students take a cognitive style test, specifically the Group Embedded Figures Test, which is a measure of Field Independence/Dependence (FI/D) (Witkin, Oltman, Raskin and Karp, 1971). FI/D is defined as "the extent to which a person perceives part of a field as distinct from the surrounding field as a whole." Students scoring high on this standardized test are characterized as analytical, imposing their own structure on material to be learned. People who score low on this measure, on the other hand, are characterized as holistic learners, preferring to learn material that is already structured. FI/D was treated as a continuous variable (FISCORE) whose values ranged from 0-18.

These individual characteristics, then, that might possibly add to the profile of students labelled as successes, failures, and dropouts included the variables of sex, age, first language, second language, time away from school, and cognitive style.

A second set of factors that were of interest to us was strategy use by our lesson participants. In the classroom, when the test for FI/D was given, students also completed a questionnaire. This questionnaire was an adapted version of the Strategy Inventory for Language Learning (SILL), (Oxford, 1990). The SILL's questions distinguish between two main types of strategies: direct strategies and indirect strategies.

The first group, the direct strategies, can be defined as those strategies that involve direct contact with language use. The direct strategies include memory, cognitive, and compensatory strategies. The first of these subgroups, memory strategies, are those that enable the student to store and access information, utilizing techniques that have been around for a long time. Examples of memory strategies include grouping, making associations, and placing new words in context. In our analysis, we named this variable MEMAV.

The second direct strategy, use of cognitive techniques, involves the manipulation or transformation of language by the learner. Examples of cognitive strategies include repeating, practicing sounds and writing, making use of formulas and patterns, recombining familiar items in new ways, skimming and scanning, taking notes, summarizing, and analyzing material. These strategies are the ones that are most familiar to students, and as a result, are the most popular. In our analysis this variable was called COGAV.

The final direct strategy involves compensation. Compensatory strategies are those that enable students to make up for where they are limited in their knowledge of a language. Compensation techniques involve using all the clues possible to understand language, whether it is the main idea in a passage or the gist of a conversation. The use of circumlocution, synonyms, and gestures to get an idea across exemplifies compensation strategies. This variable was COMPAV in our analysis.

The other main category of strategies involves those termed indirect strategies. As their name indicates, these are strategies that do not entail direct contact with language, but rather address strategies that indirectly involve language. The first of these strategies is metacognitive strategies which can be defined as those techniques that allow a student to manage his own cognition and coordinate how learning occurs. Examples include overviewing material, linking new material with what is already known, consciously deciding to pay attention, and arranging a schedule for learning. This variable was called METAV.

The second indirect strategy involves all of the affective strategies. These techniques enable one to keep a handle on his emotions, motivations, and attitudes. Examples include lowering anxiety levels when possible, using positive statements, taking wise risks, rewarding oneself for doing well, and noting when stress is too great. We called this variable AFFAV.

The last type of indirect strategy is the use of social strategies. These techniques assist learners because they involve interaction with others. Asking questions for clarification, asking for verification of what's been said, and asking for corrections exemplify social strategies that may be used in learning. SOCAV was the name of this strategy.

A final factor that we thought might account for group membership was the course information that was obtained for each student. The information that we were most interested in included semester grade point average (SEMGPA), cumulative GPA (CUMGPA), total number of credits taken for the semester (USEM), and total number of cumulative credits taken (TUCUM).

Analysis

Once all of these data were obtained for each student, along with the information stored from the computer lessons themselves, we had to ask ourselves how to best analyze this statistically. We were interested in student profiles. In order, then, to investigate the groups that had been identified (that is, the successes, the failures, and the dropouts) from the groups of variables just described, Discriminant Function Analysis was chosen as the multivariate statistic.

The major purpose of Discriminant Function Analysis according to Tabachnick and Fidell (1989) is "to predict group membership from a set of predictors" (p.505). This statistical procedure enables researchers to predict whether a set of variables can reliably predict group membership. This is basically what we wanted to do. We wanted to find a dimension among our set of variables which would enable us to define a student profile for each of the groups that we created. However, one of the assumptions of discriminant function analysis is that the number of variables multiplied by 5 should not exceed the total sample size (Tabachnick & Fidell, 1989). Since our total sample size is 158 and we have a total of 17 variables, we decided to have the least probability of error by running the discriminant funtion in four analyses. The first three analyses are based on the three categories of factors which we thought might influence group membership (individual characteristics, strategy use, and course information). Then, based on the results of these analyses, we selected the variables which discriminated the most and ran the final analysis which would enable us to define the student profiles.

Our total sample of 158 cases was divided into three groups: group 1 was labeled the success group and had 41 cases; group 2 was the failure group and had 27 cases; group 3, the dropout group, had 90 cases. Discriminant Function Analysis is robust to uneven sample sizes because it is typically a one way analysis (J. D. Petersen, personal communication, February, 1992), thus our uneven sample sizes did not create a special problem.

Results

For the first analysis, we investigated the combination of individual characteristics in terms of six variables, SEX, AGE, LG1, LG2, TMAWAY, and FISCORE. Table 1 shows the summary of the discriminant functions. Function 1, or the first combination of a set of predictors causing variance among the groups, accounted for 87% of the total variance while the second function accounted for only 13%. The canonical correlation, which is the correlation between the grouping variables and the sum of the discriminant scores on the set of predictors is .30, much higher than the second function. The Wilks' Lambda, the main statistical procedure used in the stepwise analysis, is .896 which is lower than the second function--the lower the value of Wilks' Lambda the more significant the function. Thus, you will see that the first function is significant at .002 but the second function is not significant at all.

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Insert Table 1 about here.

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The next step investigated the question, "We know that the first function is significant, but among all the variables, which accounted for the most variation?" The canonical discriminant function coefficient tells us that FISCORE has the highest beta weight, with a loading of .99. In Discriminant Function Analysis, only those variables with a loading of .3 or higher are considered to be significant. Therefore, since none among all of the other variables showed a loading of .3 or more, this means that FISCORE is the sole variable responsible for variation among the groups. Since Function 2 is not significant, the beta weights and loadings were not included in Table 1.

The second analysis was based on strategy use and as stated above, six variables were included. Function 1 accounted for 80% of the total variation with a canonical correlation of .365, a Wilks' Lambda of .833 and a significance level of .005. The second function is not significant. Looking at the beta weights and loadings, we see that though COGAV (cognitive strategies) has a beta weight of 1.116, its loading is only .34. No one variable among this set accounted for a huge part of the variation, thus we might be able to include AFFAV (affective strategies) with a loading of .28 as also an important variable. Since there is no one variable accounting for a very high loading, then, a loading of .28 might be considered sufficient (J. D. Petersen, personal communication, February, 1992).

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Insert Table 2 about here.

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The third analysis (see Table 3) dealt with the course information variables. The summary table shows that function 1 was significant as it accounted for 93% of the variance. Looking at the beta weights and loadings, cumulative GPA had the highest values. Moreover, all the rest of the variables (semester GPA, total units in that semester, and total cumulative units) were all significant with values over .3.

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Insert Table 3 about here.

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We considered the fourth analysis the most crucial since it dealt with all the variables considered important based on their loadings for significant functions. Thus we ran an analysis including the Field Independence/Dependence score which was the most important predictor for Analysis 1, the cognitive and affective strategies which were the most important predictors for Analysis 2, and the number of units taken in the semester, total number of units taken, semester GPA and cumulative GPA, which were all significant in Analysis 3.

Table 4 shows that two functions are significant. The loadings on the first function shows that the combination of all four course information variables are important predictors for group membership. In the second function, the Field Independence/Dependence score is the variable which accounted for most of the variation at .85.

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Insert Table 4 about here.

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To check the validity of the functions, we ran a plotting of the group means (known as the group centroids) based on the two functions. In Figure 1, the x axis represents the first function and the y axis represents the second function. Looking at function 1 (course information), you will notice that group 2 (Failures) and group 3 (Dropouts) are distinctly separated from group 1 (Successes). For function 2 (cognitive style)/FI/D), notice that group 2 (Failures) is separated from group 1 and group 3. So you see, different separations of groups were accounted for by different combinations of variables.

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Insert Figure 1 about here.

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Discussion

From discriminant analysis, we were thus able to define a student profile for the subjects in each group. The successful student was one who had a high semester and cumulative GPA, took a high number of units both during the semester and cumulatively, and had a high Field Independence/Dependence score. On the other hand, a student who belonged to the Failure group was one who had a low semester and cumulative GPA, had taken fewer semester and cumulative units, and had a low Field Independence/Dependence score. There was a complexity in the student profile of the Dropout group because though he had a low semester and cumulative GPA and few semester and cumulative units, his Field Independence/Dependence score was only a little bit lower that the Success group average, but much higher than that of the Failure group.

With these analyses in mind, then, how can CALL lessons address differences found among our successes, failures, and dropouts? Studies have shown that students in general are more active participants when participating in CALL lessons (Rauch, 1983). The question then, is not whether they should engage in CALL lessons, but rather how we can tailor them for the groups outlined.

With advances in programming, the CALL lessons can be designed to vary lesson presentation as the students participate in the lessons. Or, with such analyses like the ones done here, we might consider predicting "at risk" students. These students might then be monitored and/or reinforced while working on the lessons. As we are reminded by Chapelle and Mizuno (1989), we need to watch what students are actually doing while they are taking the lessons, so that we can better address their needs.

Computers are an ever increasing resource that have great promise for the future. To best utilize them to their potential, however, we must not forget that they are to assist us and that the adaptation need not be on the part of our CALL participants, but rather the adaptation can be on the part of the computer. Most of us have experienced not working well on the computer. This kind of frustration is not often addressed, since the successful students are the ones who finish the lessons, activities, etc., when working on the computer. But what about the student who has difficulty? What can we do as programmers and instructors to change his experience into one of success? In the educational system as it is today, these kinds of students do get lost in the shuffle, yet computerized individual instruction may be one way that these students can be successful, if the computer's potential is not overlooked. Why not program strategy training right into the machine, so that if a student keeps getting a wrong answer, some helpful hints are provided? What about an automatic highlighting of main ideas? In the work done by England (1989), students had to edit incorrect portions of text by highlighting the mistakes and correcting them. A study such as this can provide us with a great deal of information about what students do with text. By incorporating such techniques then, little by little, aids can be removed, as the failure and/or dropout begins to experience more and more success.

The advantages to individualizing instruction are numerous and given the importance of individual differences and uniqueness, it is no longer necessary to use one program for all students. With more information about what students are like, that is, what kind of profile describes a successful or unsuccessful student, wc can better assist students rather that forcing them into a mold of what was previously considered the ideal successful student. In the future, ideally, all students will have the chance to do well, at least where CALL lessons are concerned.

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Table 1. Discriminant Function Analysis of Individual Characteristics

Summary Table of Canonical Discriminant Functions

FUNCTION	PERCENT OF VARIANCE	CANONICAL CORRELATION	WILKS' LAMBDA	SIGNIFICANCE
1	87.23	0.302	0.896	0.002
2	12.67	0.120	0.986	0.135

Standardized Canonical Discriminant Function Coefficients (Beta Weights) and Pooled Within-Groups Correlations between Discriminating Variables and Canonical Discriminant Functions (Loadings)

	Beta Weights	Loadings
	FUNCTION 1	FUNCTION 1
FISCORE	1.005	0.99
SEX	0.029	-0.15
AGE		0.02
LG1		-0.01
LG2		0.05
TMAWAY		-0.00

Table 2. Discriminant Function Analysis of Language Strategy Use

Summary Table of Canonical Discriminant Functions

FUNCTION	PERCENT OF VARIANCE	CANONICAL CORRELATION	WILKS' LAMBDA	SIGNIFICANCE
1	79.54	0.365	0.833	0.005
2	20.46	0.195	0.962	0.312

Standardized Canonical Discriminant Function Coefficients (Beta Weights) Pooled Within-Groups Correlations between Discriminating Variables and Canonical Discriminant Functions (Loadings)

	Beta Weights	Loadings
	FUNCTION 1	FUNCTION 1
COGAV	1.116	-0.34
AFFAV	-0.709	-0.28
MEMAV		0.23
SOCAV		0.19
METAV		-0.08
COMPAV		-0.06

Table 3. Discriminant Function Analysis of Course Information

Summary Table of Canonical Discriminant Functions

FUNCTION	PERCENT OF VARIANCE	CANONICAL CORRELATION	WILKS' LAMBDA	SIGNIFICANCE
1	92.79	0.509	0.721	0.000
2	7.21	0.163	0.974	0.249

Standardized Canonical Discriminant Function Coefficients (Beta Weights) Pooled Within-Groups Correlations Between Discriminating Variables And Canonical Discriminant Functions (Loadings)

	Beta Weights	Loadings
	FUNCTION 1	FUNCTION 1
CUMGPA	1.099	0.99
SEMGPA	-0.202	0.78
USEM	0.104	0.61
TUCUM	0.006	0.46

Table 4. Discriminant Function Analysis of the Most Important Predictors of Group Membership

Summary Table of Canonical Discriminant Functions

FUNCTION	PERCENT OF VARIANCE	CANONICAL CORRELATION	WILKS' LAMBDA	SIGNIFICANCE
1	82.09	0.531	0.662	0.000
2	17.91	0.281	0.922	0.006

Standardized Canonical Discriminant Function Coefficients (Beta Weights) Pooled Within-Groups Correlations between Discriminating Variables and Canonical Discriminant Functions (Loadings)

	Beta Weights FUNCTION 1	Loadings FUNCTION 1	Beta Weights FUNCTION 2	Loadings FUNCTION 2
CUMGPA	0.894	0.94	0.094	
SEMGPA		0.78		
USEM	0.800	0.59	-0.543	
TUCUM		0.45		
FISCORE	0.095		0.915	0.85
COGAV				-0.31
AFFAV	0.341		-0.218	0.29

Group Centroids

SFD	FUNCTION 1	FUNCTION 2
1	1.04	0.07
2	-0.17	-0.63
3	-0.42	0.16

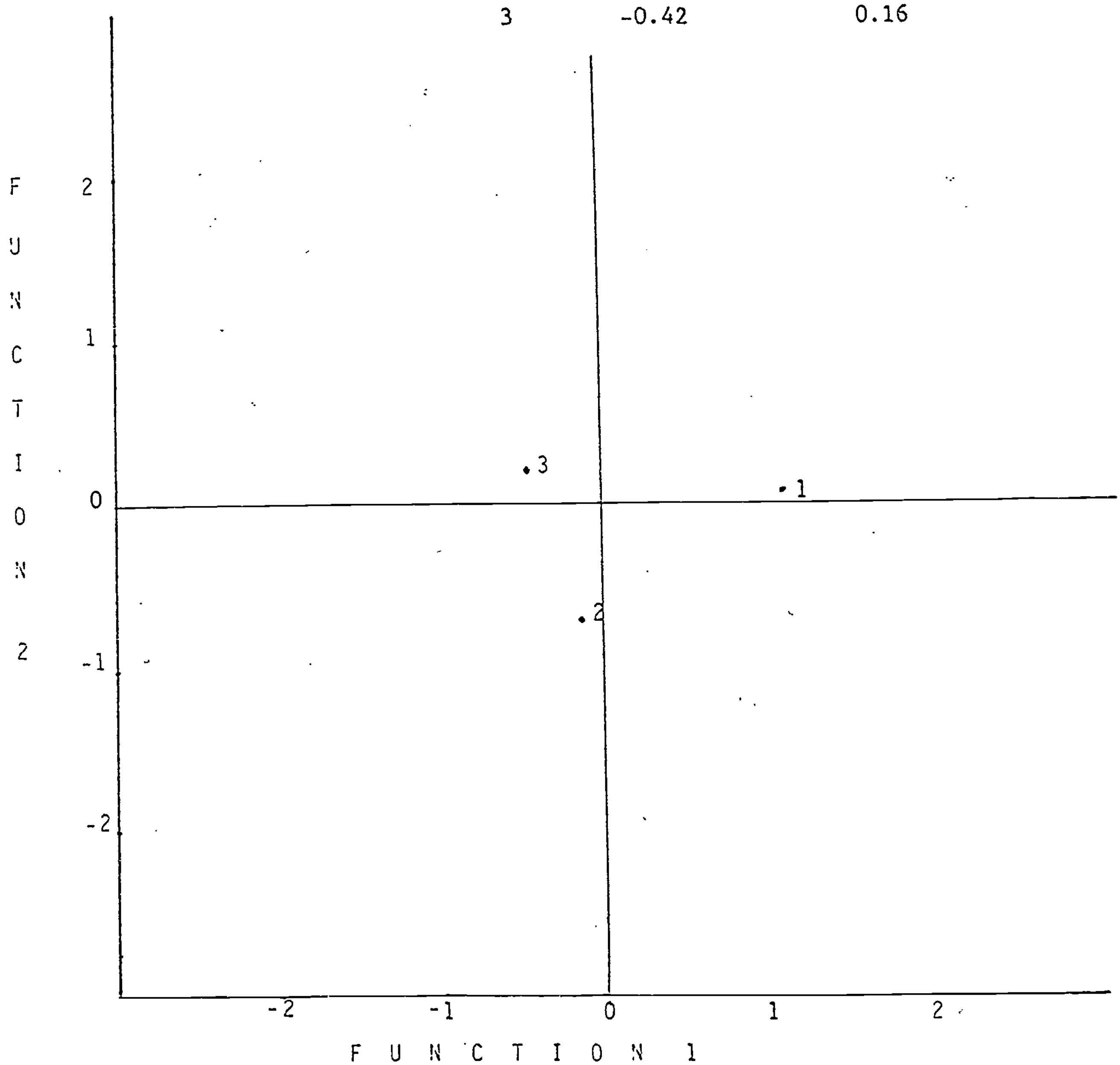

Figure 1. Canonical Discriminant Functions of the Most Important Predictors of Group Membership Evaluated at Group Means