# MARTIN-BRADLEY MODEL: DISCRIMINATE ACADEMIC PERFORMANCE BASED ON THE SELF-CONCEPT OF FRESHMEN

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**Abstract**

The Martin-Bradley Discriminant Model (MDM) was used to discriminate the academic performance of freshmen engineering students based on their self-concept scores. The modified self-concept scale, with a total of 32 items of which 8, 10, and 14 descriptors about personal worth, accepting attitudes, peer relations respectively, was used to 800 freshmen of the Don Mariano Marcos Memorial State University – Mid-La Union Campus which has an enrolment of 5875 students. Personal worth, accepting attitudes, peer relations seemed to be good criteria that can discriminate between students with low academic performance from those with high academic performance. The model indicated that students exhibiting high scores in at least two self-concept factors performed high academically and students showing low scores in at least two self-concept factors performed low academically. Among the self-concept factors, accepting attitudes was found the best indicator of academic performance.

**Keywords:** Discriminant Analysis, Self-Concept, Predictive Values, Sensitivity, Specificity, Accuracy and Error Rates

## Introduction

Discriminating Engineering freshmen students into academic performance categories based on self-concept factors opens the door to applications of discriminant analysis to categorical or qualitative variables. Particularly in the social and behavioural sciences, dichotomization frequently provides conveniences in scoring procedures and ease of interpretation of factors under investigation. This study aimed to explore the performance of Martin-Bradley discriminant method in classifying freshmen engineering students into academic performance based from their self-concepts scores. Specifically, this study sought to determine how the first-order interaction effect model of the Martin-Bradley reparametrization scheme performs in allocating freshmen Engineering students to high and low academic performance groups as determined by the median grade point average, based from their accepting attitudes, peer relations, and personal worth scores dichotomized into above and below their median scores.

Donald C. Martin and Ralph A. Bradley (1972) developed a model for joint densities of multivariate dichotomous responses. They introduced the use of orthogonal polynomials in expressing multinomial distributions or probabilities of p Bernoulli random variables. Suppose that $X_j$, j=1,2,…..$p$, represents $\boldsymbol{p}$ dichotomous random variables, each taking the values 0 and 1. The function $p_i(\underline{x})$ of the probability model is $p_i(\underline{x}) = f(\underline{x})\lfloor 1 + h(a^{(i)}), \underline{x}\rfloor$ i=1,2, **(1)** was considered where $p_i(\underline{x})$ was the multinomial density or the state probability of $\underline{x}$ in $\prod_i$ and $h(a^{(i)}, \underline{x})$ was a polynomial in the elements of $\underline{x}$ and coefficients $a^{(i)}$ were specific to$\prod_i$ .The function of $f(\underline{x})$ was defined by $f(x) = w_1 p_1(\underline{x}) + w_2 p_2(\underline{x})$ and $w_1 + w_2 = 1, w_1 \geq 0, i = 1,2$ **(2)** where the probabilities were regarded as arbitrary and assumed known if independent samples were available, or unknown but estimated if the sampling was from a mixed population.

The term $h(a^{(i)}, \underline{x})$ may be expressed in terms of orthogonal polynomials $\emptyset_t(\underline{x})$ where $\emptyset_t(\underline{x}) = 1,\ \emptyset_t(\underline{x}) = 2x_j - 1,\ j = 1,2, \ldots\ldots, p$ **(3)** $\emptyset_\tau(\underline{x}) = \prod_{j=1}^{k} \emptyset_{\tau j}(\underline{x}),$ $\tau = (\tau_1, \tau_2, \ldots.., \tau_k),\quad \tau_1 < \tau_2 < \cdots < \tau_k$ $k = 2,3, \ldots.., p\ \tau_i \epsilon \{1,2, \ldots p\}$ **(4).** The complete set of $2^k$ values of $\tau$ was denoted by $\Gamma_k$ , indicating all polynomial terms up to and including order k. The orthogonal property followed from $\sum_x \emptyset_\tau(\underline{x}) \emptyset_\lambda(\underline{x}) 2^k \Delta(\tau, \lambda)$ **(5)** $\tau, \lambda \epsilon \Gamma_k$ where $\Delta(\tau, \lambda) = 1.0\ as\ \tau \neq 1$. The set of $2^k$ polynomials $\emptyset_\tau(\underline{x}), \tau \epsilon \Gamma_k$ formed a basis for the set of all real-valued functions defined on the sample space generated by all the $x_j$ values. Thus, for any set of probability functions or state probability $p_i(\underline{x} = 1,2,)$ $h(a^{(i)}\underline{x}) = \sum_{\tau \epsilon \Gamma_k} a_\tau^{(i)} \phi_\tau(\underline{x})$ **(6)** **,** (1) and (5) showed immediately that $h(a^{(i)}\underline{x}) = \frac{p_i(\underline{x}) - f(\underline{x})}{f(\underline{x})}$ **(7)** and $a_\tau^{(i)} = 2^{-k} \sum \phi_\tau(\underline{x}) \frac{p_i(\underline{x}) - f(x)}{f(x)}$ **(8)** for i= 1,2 and $\tau \epsilon \Gamma_k$, provided $f(x) = 0$.

In the case of independent random samples available from $\prod_1\ and \prod_2$, the maximum-likelihood estimates for $p_i(\underline{x})$ were $p_i(\underline{x}) = \frac{n_i(\underline{x})}{n_i}$ **(9)** i=1,2, where $n_i$ was the sample size from $\prod_1$ and $n_i(\underline{x})$ was the frequency in state $\underline{x}$ . Further, with the prior probabilities $w_1$*, $w_2$* assumed known and specified $\hat{f}_i(\underline{x}) = w_1^* \hat{p}_1(\underline{x}) + w_2^* \hat{p}_2(\underline{x})$ **(10)** and $a_\tau^{(i)} = 2^{-k} \sum_x \phi_\tau(\underline{x}) Y^{(i)}(\underline{x})$ **(11)** where $Y^{(i)}(x) = \frac{\hat{p}_i(x) - \hat{f}(x)}{\hat{f}(x)}$ **(12)** i=1,2, again provided that $f(x) \neq 0$. Note that $w_1$* were the specified prior probability associated with $\prod_1, i = 1{,}2.$ In the case when N objects or individuals were sampled from a mixed population, the maximum likelihood estimator of $w_i$ was $\widehat{w}_i = \frac{N_i}{N}$ **(13)** where $N_i = \sum_{\underline{x}} N_i(\underline{x}), i = 1{,}2$. The maximum likelihood estimator of $p_i(\underline{x})$ was still given by $\hat{p}_i(\underline{x}) = \frac{N_i(\underline{x})}{N_i}$ **(14)** when $N_i \neq 0$. When $f(\underline{x}) \neq 0, f(\underline{x})\ and\ a_\tau^{(i)}$ retain the form of $\hat{f}_i(\underline{x}) = \widehat{w}_1\hat{p}_1(\underline{x}) + \widehat{w}_2\hat{p}_2(\underline{x})$ **(15)** and $a_\tau^{(i)} = 2^{-k}\sum_{\underline{x}} \phi_\tau(\underline{x})Y^{(i)}(\underline{x})$ **(16)** where $Y^{(i)}(\underline{x}) = \frac{\hat{p}_i(\underline{x}) - \hat{f}_i(\underline{x})}{\hat{f}(\underline{x})}, i = 1{,}2$ **(17)** when all $2^k$ parameters were estimated, the sample-based classification rule was simplified by classify $\underline{x}$ by $\prod_1$ if $\hat{h}(a^{(i)}, \underline{x}) \geq 0$ **(18)** and in $\prod_2$, otherwise $\hat{h}(a^{(i)}, \underline{x}) \geq \widehat{w}_2 - \widehat{w}_1$**(19)** if prior probabilities $w_i$ were specified and assumed equal, or classify $\underline{x}$ by $\prod_1$ if $p_i(\underline{x}) = f(\underline{x})\left[1 + h_s(a^{(i)}, \underline{x})\right]$ **(20)** and in $\prod_2$, otherwise, $h_s(a^{(i)}, \underline{x}) = \sum_{\tau\epsilon\Gamma_k} a_\tau^{(i)}\phi_\tau(\underline{x})$ **(21)** if prior probabilities $w_i$ were estimated and not assumed equal.

The potentially useful models, however, do not necessarily contain the complete expansion of $h(a^{(i)}, \underline{x})$. As proposed by Martin and Bradley, reduced models of the form may be more convenient and appropriate especially when data sets under analysis are sparse, $\boldsymbol{s}$ denotes a particular order subsets of polynomials, $h_s(a^{(i)}, \underline{x})$, selected the form $h(a^{(i)}, \underline{x})$ with terms usually corresponding to the main effects and low-order interactions. If $\Gamma_s$ denotes the set of polynomial terms up to and including order $\boldsymbol{s}$, $s \subseteq p$, p the total number of dichotomous variables, then $h_s(a^{(i)}, \underline{x})$ tends to approximate $h(a^{(i)}, \underline{x})$ by restricting $\tau\epsilon\Gamma_s$, where $\Gamma_s$ consists of those elements of $\Gamma_p$ whose polynomial terms do not exceed order s, s<p, thus reducing the number of parameters to be estimated. This is the most useful in cases when $2^p$, the number of states, is relatively greater than $n_i$ or $N_i$, the sample size of $\Pi_i$,i=1,2.

In deriving the parameter estimates for the reduced models, Martin and Bradley (1972) used maximum likelihood estimation procedures with various constraints imposed on $f(\underline{x})$ and $h_s(a^{(i)}, \underline{x})$ so that all state probabilities $p_i(\underline{x})$ are positive and sum up to unity. However, because the likelihood equations form nonlinear system and closed estimates cannot be derived, iteration methods were used. Another approach suggested by Dillon and Goldstein (1978) was to impose constraints on the complete expansion model by setting second and higher order interaction parameters to zero. Such simplification may result in $p_i(\underline{x}) < 0$ and $\sum_x p_i(\underline{x}) \neq 1$. In practice however, the likelihood ratio rule using the estimates from this simplification might still be an effective classification procedure. Athough this approach may yield reasonable error rates, like the full multinomial model, it would be of little value when many of the state frequencies will be zero.

## Methodology

The methodology in this research was adapted from the procedure used by Guirindola (1998) in his study which was also based from Pasao's (1979) extensive study. He designed, developed and constructed self-concept rating scale suitable for Filipino high school students. One of Guirindola's recommendations was to use the grade point average of freshmen college students. His respondents in his study were senior high school students but this study used the freshmen engineering students of DMMMSU – MLUC as the respondents. For the purpose of the study a questionnaire was adapted from Pasao self-concept scale with a total of 32 items of which 8, 10 and 14 statements described accepting attitudes, peer relations and personal worth respectively. Table 1 presents these descriptive statements (descriptors).

In order to avoid possible pattern in the response of the students, the self-concept descriptor statements were randomly mixed-up in the questionnaire. The questionnaire was administered to eight hundred (800) freshmen engineering students enrolled in NSTP/CWTS of DMMMSU – MLUC. The selection of the 800 sample students was done using total enumeration.

Standard test administration procedure was strictly enforced in answering the formulated questionnaire in order to elicit more or less the student's true personal preferences. Score of each student on the three (3) self-concept factors were determined and dichotomized relative to the median score in each of the factors.The grade-point average (GPA) of the 800 freshmen engineering students based from their high school final grades were requested and obtained from the Office of the Registrar. The GPA were dichotomized based from the median grade. Those whose High School's GPA were greater than the median grade 80% were categorized into High Academic Performance Group (HAPG), otherwise to Low Academic Performance Group (LAPG). The dichotomized GPA and scores on the self-concept factors constituted the base data for the discrete discriminant analysis.

Table 1. Self-concept Factors and Descriptors

| 1. ACCEPTING ATTITUDES | |
|---|---|
| a. | I accept constructive criticisms |
| b. | I accept occasional awkward moments as unavoidable |
| c. | I view failures as challenges to be met |
| d. | I treat others as I like to be treated in turn |
| e. | I consider others' welfare before my own |

| | |
|---|---|
| f. | I am a good sport |
| g. | I exercise self-control |
| i. | I am considerate and understanding of others |
| j. | I pretend to be smarter than what I really I am |
| k. | I fail to accept personal inadequacies |
| 2. PEER RELATIONS | |
| a. | I like to be with friends |
| b. | I enjoy the company of my classmates |
| c. | I am cheerful |
| d. | I make friends and adjust to people easily |
| e. | I share things with friends |
| f. | I am accepted by friends as I am |
| g. | I can deal with opposite sex |
| h. | I am popular with members of my sex |
| i. | I show sense of humor |
| j. | I talk things over with friends without inhibition |
| k. | I cooperate with others |
| l. | I am helpful and accommodating |
| m. | I have no real close friends |
| n. | I am disliked b other people |
| 3. PERSONAL WORTH | |
| a. | I think intelligently |
| b. | I like a lot of things in myself |
| c. | I have good personal taste |
| d. | I am able to cope with problems |
| e. | I want to be born again as myself if given the chance |
| f. | I would like to become more intelligent |
| g. | I am responsible |
| h. | I am conscientious |

The performance of the model was evaluated on the basis of their misclassification probabilities or error rates. Moreover, the predictive performance of the models was assessed using classification rates based from the basic structure developed by Sacket (1985) for medical use but was modified in the context of this study. Table 2 facilitated the computation of pertinent measures for predictive performance of the models.

Table 2. Basic structure for evaluation of the model's predictive performance

| | | ACTUAL ACADEMIC PERFORMANCE | | |
|---|---|---|---|---|
| | | HAPG | LAPG | TOTAL |
| PREDICTIVE ACADEMIC PERFORMANCE | HAPG | True Positive (a) | False Positive (b) | a + b |
| | LAPG | False Negative (c) | True Negative (d) | c + d |
| | TOTAL | a + c | b + d | N |

Estimation of Parameters and Error Rates of the Martin-Bradley Reparametrization Procedure

1. Determine the frequencies in each state and record the results in tabular form
2. In the case when N objects or individuals were sampled from a mixed population, estimate the maximum likelihood estimator of $w_i$ using formula (13) $w_i = \frac{N_i}{N}$ $where\ N_i = \sum_{\underline{x}} N_i(x),\ i = 1, 2$
3. The maximum likelihood estimator of $p_i(\underline{x})$ was estimated using formula (14) $p_i(\underline{x}) = \frac{N_i(\underline{x})}{N_i}$.
4. Compute $Y^i(\underline{x}) = \frac{\widehat{p_i}\,(\underline{x}) - \widehat{f_i}\,(\underline{x})}{\widehat{f_i}\,(\underline{x})}$ $, i = 1, 2$ using formula (17)
5. Compute the coefficient of the Martin-Bradley model $a_r^{(i)} = 2^{-k} \sum_{\underline{x}} \emptyset_r(\underline{x}) Y^i(\underline{x})$ using formula (16).
6. Classify the samples using the sample-based classification rules of formula (18) – (19).
7. Compute the error rate.

**Results and discussion**

Two groups of freshmen engineering students were formed based on their general point average (GPA) for the fourth year subjects. The GPAs were arrayed and cut-off point was set at the median value of 80 percent. Those whose fourth year averages were greater than 80% belonged to the High Academic Performance Group (HAPG). Otherwise the student was categorized to Low Academic Performance Group (LAPG). Total enumeration for 800 freshmen engineering students was taken and used for validation purposes of the model derived. The selected freshmen students were listed. The validation set wherein the models were applied and tested for predictive performance consisted of the 800 freshmen engineering students from which 412 belong to the LAPG and 388 to the HAPG. The distribution of the academic performance groups in the two separate data sets is presented in Table 3.

Each of the 800 selected students was asked to rate statements defining the three factors of self-concept. Note that those three factors were accepting attitudes (AA), peer relations (PR), and personal worth (PW), each containing 8, 10, and 14 statements describing related behavior, respectively. Each statement was rated according to the degree of agreement to such using the following categories: never, rarely, sometimes, often and always was cored 1, 2, 3, 4, and 5, respectively. For positive statements, the higher the frequency of the behavior described, the higher the score. For the negative items, the less frequent the behavior, the higher the score; thus scoring was reversed. To obtain the factor score, the points for the statements describing the factor were summed up. Hence, a large factor score indicated higher tendency to positively display the factor behavior. A small factor score showed otherwise once the factor scores were obtained, each student was rate dichotomously: whether or not his score exceeded the corresponding median factor score. Thus, the following binary variables were created:

$$AA = \begin{cases} 1, & if\ accepting\ attitude\ factor\ score\ exceeds\ the\ median\ 39 \\ 0, & otherwise \end{cases}$$

$$PR = \begin{cases} 1, & if\ peer\ relations\ factor\ score\ exceeds\ the\ median\ 55 \\ 0, & otherwise \end{cases}$$

$$PW = \begin{cases} 1, & if\ personal\ worth\ factor\ score\ exceed\ the\ median\ 36 \\ 0, & otherwise \end{cases}$$

Although Pasao did not use the median in computing the self-concept factor standardized rating, it was used in this study as basis in forming the dichotomy of the self-concept factors to be consistent with that in forming the dichotomy of the grade-point averages.

With these binary factors, the students in both groups, HAPG and LAPG, were classified according to the various states. With three binary factors, $2^3 = 8$ configurations of 0's and 1's were set.

The first listed state (1 1 1) corresponds to higher tendency to positively exhibit all three factors. The state (0 0 0) depicts lower tendency to positively display all three factors. For these states, there appeared to be a contrast between the two groups in the training set. LAPG had only 8.76% for (1 1 1), as opposed to HAPG's 30.92%. For the (0 0 0) state, LAPG registered a relative percentage of 37.45% and only 10.44% for HAPG. The reverse extreme state APG relationship indicated a possible use of these self-concept factors in discriminating students into these performance groups. In between the extreme state, (1 1 1) and (0 0 0), the relative frequency distribution for both groups did not show obvious contrast but some patterns can be discerned. It was very clear that the HAPG tended to positively display the factor more than the LAPG. This consistent pattern further reinforced the plausibility of using these self-concept factors as discriminants to academic performance.

The procedure used to derived discrete discriminant model was the Martin-Bradley approach. It utilizes orthogonal functions to affect classification. The interaction effect model of Martin-Bradley reparametrization included the dichotomized variables; accepting attitudes (AA), peer relations (PR), and personal worth (PW).

The assumption of equal prior probabilities for the both LAPG and HAPG was not considered since no information was available on the prior distribution or grouping of the sample students according to their academic performance. Instead, prior probabilities were estimated from the sample proportions and they were $w_1 = 0.0502$ and $w_2 = 0.498$ for LAPG and HAPG, respectively. With these prior probability estimates, parameter estimates for the intersection effect model were calculated yielding the following results.

Considering the magnitudes of the coefficients, $a_1^{(1)}$ and $a_2^{(2)}$ were relatively large, it seemed to indicate the relative importance and high dependence of academic performance on accepting attitudes (AA) factor of self-concept of the students. Although $a_1^{(1)}$ or $a_2^{(2)}$ and $a_3^{(2)}$ are not as large as $a_1^{(1)}$ or $a_1^{(2)}$, their magnitudes appeared enough to consider peer relations (PR) and personal worth (PW) as indicators of self-concept in discriminating the academic performance of the students. In the absence of statistical test suggested by Martin-Bradley to test parameter estimates, this study relied on the results of Pasao's extensive study on self-concept which included the three (3) factors (namely, accepting attitudes, peer relations and personal worth) among the main indicators of self-concept. Among the parameters having magnitude smaller than the ones cited above are $a_{23}^{(1)}$ or $a_{23}^{(2)}$, the coefficients representing the interaction between peer relations (PR) and personal worth (PW), has the lowest value. It may have have insubstantial effect on the interaction between on (PR) and (PW) on the academic performance of the students.

Plugging in the coefficients estimates shown in Table 3, the discrete discriminant interaction effect model of the Martin-Bradley reparametrization had the form

$p_1(\underline{x}) = f(\underline{x})[1+(-0.0405 - 0.2286x_1 - 0.1507x_2 - 0.1680x_3 + 0.0589x_{12} - 0.0168x_{13} + 0.00006x_{23})]$

$p_2(\underline{x}) = f(\underline{x})[1+(0.0408+0.2305x_1+0.1520x_2+0.1694x_3+0.0593x_{12} - 0.0169x_{13} + 0.00006x_{23})]$

where $f(\underline{x}) = \sum_{i=1}^{2} wi(\frac{Ni(x)}{Ni}), i = 1, 2$ and Xij $= \begin{cases} 1, x_{ij} = 1 \\ -1, otherwise \end{cases}$

Table 3. Parameter estimated for the interaction effect model of the Martin-Bradley reparametrization

| PARAMETRIC / COEFFICIENT | ACADEMIC PERFORMANCE GROUP | |
|---|---|---|
| | LOW ($\prod_1$) | HIGH ($\prod_2$) |
| $\tilde{a}0$ | - 0.0405 | 0.0408 |
| $\tilde{a}1$ | - 0.2286 | 0.2305 |
| $\tilde{a}2$ | - 0.1507 | 0.1520 |
| $\tilde{a}3$ | - 0.1680 | 0.1694 |
| $\tilde{a}12$ | 0.0589 | - 0.0593 |
| $\tilde{a}13$ | - 0.0168 | 0.0169 |
| $\tilde{a}23$ | - 0.00006 | 0.00006 |

Using the parameter estimates above, the first-order interaction effects model of the Martin-Bradley reparametrization scheme allocated the different state into two academic performance groups (the LAPG and HAPG) using the classification rule for unequal and estimated prior probabilities, that is, classify as LAPG if, $\hat{h}(a^{(1)}, \underline{x}) \geq \hat{w}_2 - \hat{w}_1 \geq 0.489 - 0.502 \geq -0.004$ and in HAPG otherwise.

Table 4. Classification Performance of the First-Order Interaction Model of the Martin-Bradley Reparametrization at Various States

| STATE | | | $\hat{h}_S(a^{(1)}, \underline{x})$ | CLASSIFICATION (0-LAPG,1-HAPG) |
|---|---|---|---|---|
| AA | PR | PW | | |
| 1 | 1 | 1 | -0.5458 | 1 |
| 1 | 1 | 0 | -0.1761 | 1 |
| 1 | 0 | 1 | -0.3619 | 1 |
| 1 | 0 | 0 | 0.0075 | 0 |
| 0 | 1 | 1 | -0.1728 | 1 |
| 0 | 1 | 0 | 0.1298 | 0 |
| 0 | 0 | 1 | 0.2466 | 0 |
| **0** | 0 | 0 | 0.5489 | 0 |

As shown in Table 4is the results of the allocation. Students with the states (1 1 1), (1 1 0), (1 0 1), and (0 1 1) were allocated to HAPG while those belonging to the states (0 0 0), (0 0 1), (0 1 0), and (1 0 0) were classified into LAPG. This seemed to indicate that a student who displayed higher positive tendency in at least two of the self-concept factors would be classified with the HAPG, while a student who showed lower positive tendency in at least two of the factors would be classified with the LAPG.

The model incorrectly classifies 27.17% of the engineering students. This seemed to tell that based from the sample, the model incorrectly classifies 27.17% of the students. The model's sensitivity and specificity rate are 56.7% and 88.35% respectively. Sensitivity identifies a student with has a high academic performance while specificity correctly classify student who performed low academically. The model's positive predictive value (PPV) and negative predictive value (NPV) are 82.09% and 68,42%, respectively. PPV indicates the proportion of engineering students who performed high academically while NPV indicates the proportion of engineering students who performed low academically. The model produced an accuracy rate of 73% which measures the overall rate of agreement between the model and the actual outcome. Shown in Table 5 is the predictive academic performance of the model.

Table 5.Predictive academic performance outcome of the model

| | | ACTUAL ACADEMIC PERFORMANCE | | |
|---|---|---|---|---|
| | | HAPG | LAPG | TOTAL |
| PREDICTIVE ACADEMIC PERFORMANCE | HAPG | 220 | 48 | 268 |
| | LAPG | 168 | 364 | 532 |
| | TOTAL | 388 | 412 | 800 |

The Martin-Bradley discriminant model generated in this study all included accepting attitudes (AA), peer relations (PR), and personal worth (PW). Their parameters were estimated from the training set composed of

800 sample engineering freshmen students. Within this set, the models with their corresponding classification rules allocated the students who were grouped the LAPG and HAPG as shown in Table 6.

The high error rates could have largely been influenced by having too few variables / parameters in the models. As pointed out by Dillon and Goldstein (1978), simplification of the models may yield reasonable error rates. Wasson (1995) and Guirindola (1998) pointed out likewise that the error rate will almost always be higher when a model is used prospectively in a new group. The models failed to demonstrate such phenomenon.

Table 6. Classification performance of discrete discriminant models at various states

| STATE | | | MARTIN BRADLEY MODEL |
|---|---|---|---|
| AA | PR | PW | |
| 1 | 1 | 1 | HAPG |
| 1 | 1 | 0 | HAPG |
| 1 | 0 | 1 | HAPG |
| 1 | 0 | 0 | LAPG |
| 0 | 1 | 1 | HAPG |
| 0 | 1 | 0 | LAPG |
| 0 | 0 | 1 | LAPG |
| 0 | 0 | 0 | LAPG |

Accepting attitudes, peer relations and personal worth seemed to discriminate well between low academic performance and high academic performance groups. The models uniformly indicated that students exhibiting high scores in at two self-concepts factors performed high academically. Among the self-concept factors, accepting attitudes was found the best indicator of academic performance. The first-order interaction effects model of Martin-Bradley reparametrization likewise showed the importance of this factor with a relatively high coefficient of the marginal parameter a1.

In general, the Martin-Bradley discriminant model can be used as a rough guideline or warning signal to students' needs and problems.

## Recommendatıons

The results can be used as basis for discriminating students to be enrolled in Math plus and English plus. For further studies of this nature, it may help to investigate the aptness of the discrete discriminant models specifically the Martin-Bradley procedure to predict the performance of engineering students in the Licensure Examination. Other threshold point based from Pasao's standard self-concept rating scheme may be used as basis for dichotomizing the self-concept indicators. Variation of models of the different procedures of discrete discriminant analysis should also be explored to allow comparison of models within procedure and provide wider spectrum of comparison among procedures. It may be more interesting and logical to use grade-point average on the first semester of freshmen student to represent academic performance and his/her self-concept measured during the same semester of the said school year.

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