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The Early Identification of At-Risk Students in an Undergraduate Marketing Metrics Course

Bruce K. Pilling
Georgia State University, bpilling@gsu.edu

David L. Nasser
Georgia State University, nasser@gsu.edu

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Bruce K. Pilling, Georgia State University

bpilling@gsu.edu

David L. Nasser, Georgia State University

nasser@gsu.edu

Abstract - This research describes the development of a diagnostic tool to permit the early identification of at-risk students in an undergraduate marketing metrics course. Using multiple discriminant analysis, students were classified into performance categories by drawing on a set of predictor variables conceptually linked to student performance in math-based courses. The discriminant model included math ability, perceived self-efficacy, math anxiety and overconfidence as potential discriminators of student performance. The model successfully identifies at-risk students at three times the chance probability. The early identification of at-risk students is a critical first step in the process to improve student performance.

Note: The authors failed to provide KeyWords and a statement regarding the Relevance of their work to Marketing Educators, Researchers and/or Practitioners.

Introduction

Recognition of the importance of analytical skills for marketing graduates has led to an increased teaching emphasis on these skills. Saber and Foster (2010), Ganesh, Sun and Barat (2010), and Pilling, Rigdon and Brightman (2012) each report on the development and introduction of stand-alone marketing analysis courses. The value that employers place on marketing graduates who possess

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these skills has contributed to the emphasis on analytical skills (Schlee and Harick, 2010). For example, Finch, Nadeau and O'Reilly (2012) report that the top practitioner priority for marketing education was return on investment analysis. As well, the marketing literature has established the value of quantitative analysis in marketing decisions (Kumar and Shah, 2009).

A key reason for an increased teaching emphasis on analytical skills is to address deficiencies that have been identified in marketing students and marketing graduates (Remington, Guidry, Budden and Tanner, 2000; Aggarwal, Vaidyanathan and Rochford, 2007; and Saber and Foster, 2011). Analytical deficiencies can be attributed to insufficient emphasis on analysis in the marketing curriculum and to in-coming marketing student attributes, such as levels of motivation, interest, ability, prior knowledge and preparation related to analysis (Kennedy, Lawton and Plumlee, 2002; LaBarbera and Simonoff, 1999; and Remington et al. 2000). Aggarwal et al. (2006) show that compared to finance, accounting, MIS and management, marketing majors score lower on both ACT and SAT math scores as well as on a merit index composed of ACT/SAT scores, high school GPA and high school curriculum rigor. In addition to ability, an enduring stereotype is that some students choose the marketing major as a refuge from numbers (Hugstad, 1997; LaBarbera and Simonoff, 1999). Students may struggle to apply analytical concepts presented in foundation courses to marketing decisions (Remington et al., 2000). Marketing students may not initially appreciate the value of quantitative analysis in marketing decisions (Saber and Foster, 2010) and may also experience difficulty with basic marketing math (Ganesh, Sun and Barat 2010). Marketing students can struggle to acquire analytical skills and marketing educators face challenges in helping their students acquire these skills.

The level of student performance in a required undergraduate marketing metrics course at a large public southeastern university appears to reflect many of these challenges. The university tracks the percentage of students who receive letter grades of D or F or who withdraw (W) from a given course. The DFW rate in the required undergraduate marketing metrics course is about triple the DFW rate across all of the courses offered in the marketing department. At the individual student level, it is believed that there is a significant opportunity to help at-risk students by identifying them at the beginning of the semester. Drawing on a medical analogy, early diagnosis is often the first critical step in treatment or prevention. As an example, a diagnosis of pre-diabetes leads to recommendations of changes in diet and exercise. The sooner the correct diagnosis is made, the greater is the likelihood to avoid or significantly delay the onset of type 2 diabetes. Similarly, the early diagnosis of at-risk students is a critical first step in helping students to succeed in a course.

The purpose of the present study, then, was to develop a diagnostic tool to permit the early identification of at-risk students in an undergraduate marketing metrics course. Using multiple discriminant analysis, a model to classify students into performance categories was developed and validated by drawing on a set of variables conceptually linked to student performance in math-based courses. The model included math ability, perceived self-efficacy, math anxiety and overconfidence as possible discriminators of student performance. The remainder of the article is organized as follows. The next section introduces the individual difference variables that were considered to classify students into performance categories. The study methodology is then described, which includes information on the sample, measures, and the development and validation of the discriminant model. The discriminant results are discussed and suggestions for implementing the approach are provided.

Study Variables

Given the purpose of the study, candidate independent variables were selected based on their linkage to student performance in math-based courses in prior research. The selected study variables were math ability, perceived self-efficacy, math anxiety and overconfidence.

Math Ability

Math ability can been described as the power to solve math problems (Gallagher and De Lisi, 1994). In the current research context, math ability is viewed as the power to solve marketing problems through the application of math concepts. Math ability includes a capacity or aptitude component, capturing an innate capability related to math (Siegel, Galassi, and Ware, 1985). Ability also includes a skills component, reflecting the capability to apply one's underlying capacity (Gallagher and De Lisi, 1994). This component is sometimes referred to as math reasoning or developed ability (College Board, 2011). This conceptualization is consistent with the College Board's interpretation of the SAT math component. According to the College Board (2011, p. 4) the math component of the SAT measures the ability to "apply strong problem-solving techniques" and to use math "in flexible ways". Stated differently, the SAT math score reflects both the student's math aptitude and math skills related to the correct application of math knowledge. In the mathematics education literature, Siegel et al. (1985) found that mathematics performance was predicted by ability. In accounting, Eskew and Faley (1988) report that ability improved performance in the first college-level financial accounting class. Borde (1988) found that prior GPA (believed to include an ability component) was a predictor of success in the introductory marketing course.

Self-Efficacy

Self-efficacy captures the extent to which an individual believes that he or she can organize and execute the necessary resources to achieve a given outcome.

For example, does a student believe that he/she has the capability to mobilize the resources required to solve a homework problem, to pass an upcoming exam or to pass a course? Self-efficacy "…is concerned not with the skills one has but with the judgments of what one can do with whatever skills one possesses" (Bandura, 1986, p. 391). Therefore, a student's capability perceptions to apply skills will subsequently influence that student's behavior, motivation, persistence, emotions and thoughts (Gist and Mitchell, 1992). As reviewed by Farrell (2006), self-efficacy correlates positively with setting higher goals, remaining task-oriented in the face of setbacks, and with levels of motivation and effort related to goals in educational settings. Self-efficacy has been linked to math performance in numerous studies (Pajares and Miller, 1994; Siegel et al. 1985). In the marketing education literature, self-efficacy has been studied in the context of course selection and effort in class (Lancellotti and Thomas, 2009), critical thinking identity (Celuch, Kozlenkova, and Black, 2010), and the impact of experiential assignments on self-efficacy (Lilly and Pollack, 2008).

Math Anxiety

Math anxiety has been described as "feelings of tension and anxiety that interfere with the manipulation of numbers and the solving of math problems in a wide variety of ordinary life and academic situations" (Richardson & Suinn, 1972, p. 551). Math anxiety has been linked to physiological, cognitive and behavioral responses in students, such as avoiding a math class or experiencing a sense of panic in attempting to solve a math problem. Math anxiety can lead to negative cognitions, avoidance behavior and decreased performance on math problems (Hopko, Mahadevan, Bare, and Hunt 2003). Because marketing students may have difficulty with marketing math (Ganesh, Sun and Barat 2010) , may select the major to avoid math (Hugstad, 1997; LaBarbera and Simonoff, 1999) or may not realize the importance of math within marketing (Saber and Foster, 2010), it is plausible that math anxiety may play a role in identifying at-risk students.

Overconfidence

Marketing students generally overestimate their examination performance and their final course grades. Students with lower grades overestimate their grades to a greater extent than students with higher grades (Kennedy et al. 2002). This phenomenon has been referred to as overconfidence or blissful ignorance and is negatively correlated with grades (Clayson, 2005). Student perceptions of their expected course performance at the start of the semester would reasonably be expected to influence study habits, time spent on the course and learning strategies. Overconfident students, therefore, would be less likely to engage in effective learning strategies (Grimes, 2002). The overconfidence effect has been attributed to a lack of the necessary meta-cognitive skills to recognize incompetence (Kruger and Dunning, 1999; Kennedy et al. 2002), misplaced expectations (Clayson, 2005) and optimism (Svanum and Bigatti, 2006). Overconfidence may negatively impact the at-risk student in two ways. At-risk students are more likely to be overconfident when compared to students with higher grades and are therefore more likely to suffer the negative consequences of overconfidence (Grimes 2002). For example, overconfident students may get off to a poor start in the course due to lack of effort, perhaps linked to a misperception of their level of competence. Overconfidence may also delay students' recognition of their jeopardy in the course and the need to change their approach. Second, at-risk students have a smaller margin for error in order to succeed in the course.

Method

Multiple discriminant analysis was selected as the primary analytical technique to develop the diagnostic tool. One purpose of MDA is to classify future observations into pre-determined groups (Sharma 1996). This purpose is consistent with the study objective to identify at-risk students through the classification of students at the beginning of the semester to performance categories.

Sample

Data were collected from students enrolled in eight sections of an undergraduate marketing metrics course from the fall 2010 semester through the spring 2012 semester at a large public southeastern university in the United States. All sections were taught by the same instructor. During the second class period of the term, students were invited to participate in a voluntary research study. The questionnaires were not administered by the teacher, but by a research colleague. The teacher did not have access to the questionnaires until after the end of the term, thereby protecting students' privacy. Students received no incentive to participate. A total of 162 students completed the questionnaires, with 3 declining participation. Students completed the self-efficacy questionnaire followed by the math ability and math anxiety questionnaires.

Measures

Self-efficacy

Self-efficacy measures should be context-specific (Bandura, 1984; Parajes and Miller, 1994). Because self-efficacy captures an individual's belief that he/she can succeed at a specific task, the measure must necessarily be adapted to the task in question. Context-specific measures of self-efficacy increase its predictive power (Kuo and Hsu, 2001). Consistent with Pajares and Miller (1994), a set of problems to capture math self-efficacy was developed. The goal was to measure students' perceptions of their confidence to solve math problems related to the type of math used in the marketing metrics course. A 20 item instrument was developed, focusing on math concepts including probability, ratios, slope, and percentage change. The following is a sample question:

"Stephanie bought a sweater for $42.40, including a 6% sales tax. What was the price before tax?" Students were asked to read each question and to indicate, with 1 = No Confidence at All and 5 = Complete Confidence, their level of confidence to give the correct answer to each question. Each student's self-efficacy score was calculated by adding up their level of confidence for all twenty questions. Self-efficacy scores could range, therefore, from 20 (no confidence) to 100 (complete confidence). The self-efficacy scale had a coefficient alpha of .89. Perceived self-efficacy scores ranged from 40 to 100, with a mean of 74.5. Students were fairly confident in their ability to solve the metrics problems. An average score of 60 would indicate "some confidence" (the midpoint of the scale), while an average score of 80 would indicate "much confidence".

Math Ability

Similar to self-efficacy measures, ability measures should be context-specific. The math ability instrument focused on the math aptitude and skills necessary to master the marketing metrics taught in the new course. Following Bandura's (1986) guideline, the assessment of math ability used the same 20 problems on which self-efficacy was measured. Using the same sample question: "Stephanie bought a sweater for $42.40, including a 6% sales tax. What was the price before tax?", the student would choose from the following answers: a. $39.86; b. $40; c. $40.44; d. $41 or e. $44.94. Students were given 30 minutes to answer the 20 multiple choice questions. Performance was calculated as the number of correct answers minus one-quarter point for each incorrect answer. This approach produced a scale that could range from -5 to 20 points. Scores ranges from 0 to 18.75 with a mean score of 8.4. Coefficient alpha was .74.

Math Anxiety

Math anxiety was measured using the Abbreviated Math Anxiety Scale (Hopko et al., 2003). This scale was developed to measure anxiety in math-related situations and was tested on a large sample of university undergraduates. The scale captures two dimensions of math anxiety; learning math anxiety and math evaluation anxiety. Because the current study focuses on the student's ability to apply math concepts to marketing problems, the math evaluation anxiety dimension of the Abbreviated Math Anxiety Scale was used. Students were asked to rate their level of anxiety, with 1 = Low Anxiety and 5 = High Anxiety, when faced with various situations, such as "Thinking about an upcoming math test 1 day before" or "Being given a homework assignment of many difficult problems that is due the next class meeting". While the marketing metrics course is not a traditional math class, the course requires the application of algebra to marketing problems. Because the AMAS was developed to capture math evaluation anxiety in "math-related" situations, it was selected as an appropriate scale. Math anxiety scores ranged from 1 to 5, with a mean of 3.6 and a coefficient alpha of .85.

Overconfidence

An overconfidence measure was created in the following manner, based on the approach recommended by Pajares and Miller (1994). For each of the 20 questions on the math ability test, the student's level of confidence to answer the question correctly was compared with the student's answer. For a given question a student was judged to be overconfident when the question was answered incorrectly and the student had previously rated his/her confidence to answer the question correctly as either 4 (Much Confidence) or 5 (Complete Confidence). An overall overconfidence score was calculated by summing the total number of questions for which the student was judged to be overconfident. This approach created a scale with a possible range from 0 to 20 points. Overconfidence scores varied from 0 to 12, with a mean of 4.9. On average students answered about 5 questions, for which they were highly confident, incorrectly.

Student Performance

Consistent with multiple discriminant analysis, a categorical dependent variable was created using student performance data. Individual student performance was initially measured by calculating each student's average score across four equally weighted semester exams. In order to facilitate the research objective, a categorical dependent variable was created by splitting individual student performance data into 5 equal categories. A quintile approach was chosen for several reasons. Grading and course registration data from the eight sections of the course that made up the sample suggested that roughly 20% of the students were at-risk. About 13% of the students failed the course (10% Ds and 3% Fs.) Around 8% of the students initially registered for the course withdrew before the midterm of the semester (the withdrawal deadline). It is reasonable to assume that some of the withdrawals were due to poor performance and perceived risk of failing the course. Finally, about 10% of the sample received a grade of C-, suggesting that some of that group could also legitimately be characterized as at-risk. A second reason for using a quintile approach was to provide the opportunity to compare differences across the categories to help better understand the at-risk student category. Dividing the sample into five categories permits the comparison of differences across more categories and may help to better understand the at-risk student category.

There were three reasons for not using student letter grades as the dependent variable. The final course grade included a teamwork component that could mask the identification of at-risk students (who would have potentially failed the course without the benefit of the teamwork grade). Second, while the assignment of course grades was guided by a standard letter grading scale, the instructor also took into account naturally occurring breaks in the grading data. Finally, in several instances students whose grades were marginal did in fact receive "passing" grades for the course, reflecting the difficulty of "failing too many students" in a given section of the course. Using individual student test scores rather than final course grades avoided this problem because the individual test scores did not reflect this bias. Table 1 presents data on the study variables, including correlations, means and standard deviations.

Table 1: Correlations Across Study Variables

	Math Ability	Self-Efficacy	Math Anxiety	Over Confidence	Performance
Math Ability	1				
Self-Efficacy	.48*	1			
Math Anxiety	-.40*	-.39*	1		
Overconfidence	-.41*	.42*	.02	1	
Performance	.57*	.29*	-.25*	-.27*	1
Mean	8.4	74.5	3.6	4.9	3
SD	4.2	11.2	1.0	2.6	1.4

Total Sample = 162
* Significant at .01 level (1-tailed)

Developing the Discriminant Model

The research goal was to develop a discriminant function that would be used to identify at-risk students at the start of a given semester. Using the direct command in SPSS, all of the predictor variables were used to calculate the discriminant functions. Because the set of predictor variables was relatively small and linked to student performance in prior research, all of the variables were included in the analysis (Hair et al. 1992). The results of the discriminant analysis are presented in Tables 2, 3 and 4. Table 2 presents information on the equality of group means for each predictor variable across the five performance categories. The F test is significant for each independent variable, suggesting that the means of the five performance categories differ significantly for each independent variable.

Table 2: Tests of Equality of Group Means

Independent Variables	Wilks' Lambda	F	D.F.	Significance
Math Ability	.648	21.2	4,156	P < .001
Self-Efficacy	.91	4.0	4,156	P = .004
Math Anxiety	.92	3.5	4,156	P = .008
Overconfidence	.84	7.2	4,156	P < .001

The assumption of homogeneity of covariance matrices of the performance groups was met (Box's M = 52.9, p = .14.) Table 3 includes information on the canonical discriminant functions and the significance tests of the discriminant functions.

Table 3: Summary of Canonical Discriminant Functions

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	.621	88.0	88.0	.619
2	.064	9.1	97.1	.245
3	.018	2.6	99.7	.134
4	.002	.3	100.0	.047

Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	Df	Sig.
1 through 4	.568	87.9	16	P < .001
2 through 4	.921	12.8	9	P = .171
3 through 4	.980	3.2	4	P = .532
4	.998	.35	1	P = .555

Only the first function was statistically significant at alpha = .05 (Wilks' Lambda .568, X2 = 87.9, (p > .001) and accounted for 38% of the variance in the performance variable (the square of canonical correlation). The second discriminant function was not significant at alpha = .05 (Wilks' Lambda .921, X2

= 12.8, p = .171.) The second function accounted for an additional 6% of the variance in the performance variable. While this function was not significant at alpha = .05, following Hair et al. (1992, p. 99) the function was examined to assess its potential value in further describing the at-risk student. The classification matrix is presented in Table 4.

Table 4: Classification Results

		Predicted Group Membership					Total
		1	2	3	4	5	
Actual Group[1]	1	n=19 61.3%	n=4 12.9%	n=6 19.4%	n=2 6.5%	n=0 0%	n=31
	2	n=5 15.2%	n=11 33.3%	n=7 21.2%	n=4 12.1%	n=6 18.2%	n=33
	3	n=9 28.1%	n=7 21.9%	n=9 28.1%	n=2 6.3%	n=5 15.6%	n=32
	4	n=6 18.2%	n=9 27.3%	n=4 12.1%	n=6 18.2%	n=8 24.2%	n=33
	5	n=1 3.1%	n=4 12.5%	n=2 6.3%	n=4 12.5%	n=21 65.6%	n=32

[1] 41.0% of actual cases are correctly classified.

Forty-one percent of the sample was correctly classified. According to Hair et al. (1992), the classification rate should represent an improvement of at least 25% over the chance rate. In this case the classification rate is more than double the chance rate of 20%. To assess the classificatory power of the discriminant model Press's Q statistic was calculated. Press's Q compares the classification results to those expected by chance. The results indicate that the solution is statistically better than chance (Q = 43.6, 1 d.f., P< .01).

External Validation of the Discriminant Function

The U-method was used to validate the discriminant function. This method estimates k – 1 samples, by eliminating one observation at a time from the sample of k cases. Based on Rencher (1994) the U-method provides the most accurate and consistent assessment of the classification accuracy rate. Rencher (1994) also points out the U-method is superior to using a hold out sample because "the holdout sample approach doesn't evaluate the classification function we will used in practice" p. 310). This method focuses on classification accuracy, which is consistent with the research objective of the paper (Hair et al. (1994). The results are presented in Table 5.

Table 5: Validation Results

		Predicted Group Membership					Total
		1	2	3	4	5	
Cross-validated[1]	1	n=18 58.1%	n=5 16.1%	n=6 19.4%	n=2 6.5%	n=0 0%	n=31
	2	n=6 18.2%	n=10 30.3%	n=7 21.2%	n=4 12.1%	n=6 18.2%	n=33
	3	n=9 28.1%	n=7 21.9%	n=9 28.1%	n=2 6.3%	n=5 15.6%	n=32
	4	n=6 18.2%	n=11 33.3%	n=5 15.1%	n=3 19.1%	n=8 24.2%	n=33
	5	n=1 3.1%	n=4 12.5%	n=2 6.3%	n=5 15.6%	n=20 62.5%	n=32

[1] 37.3% of actual cases are correctly classified.

The U-method gave a correct classification rate of 37.3%. As expected, this rate was somewhat lower than the 41% from the analysis sample. The 37.3% classification rate was about 86% better than the chance classification rate and had a Press's Q of 30.0 (1 d.f., ($p < .01$).

Given the statistically significant classificatory power of the discriminant function, the classification rates for the five performance categories were then examined. The classification rate for each of the five performance groups was tested by calculating its appropriate Z score (Huberty, 1984). These results are presented in Table 6.

Table 6: Significance of Classification Rates for Performance Groups

	Performance Groups				
	1	2	3	4	5
Z Score[1]	5.75, $p < .001$	1.91, $p = .028$	1.16, $p = .087$	-.25, $p = .40$	6.26, $p < .001$

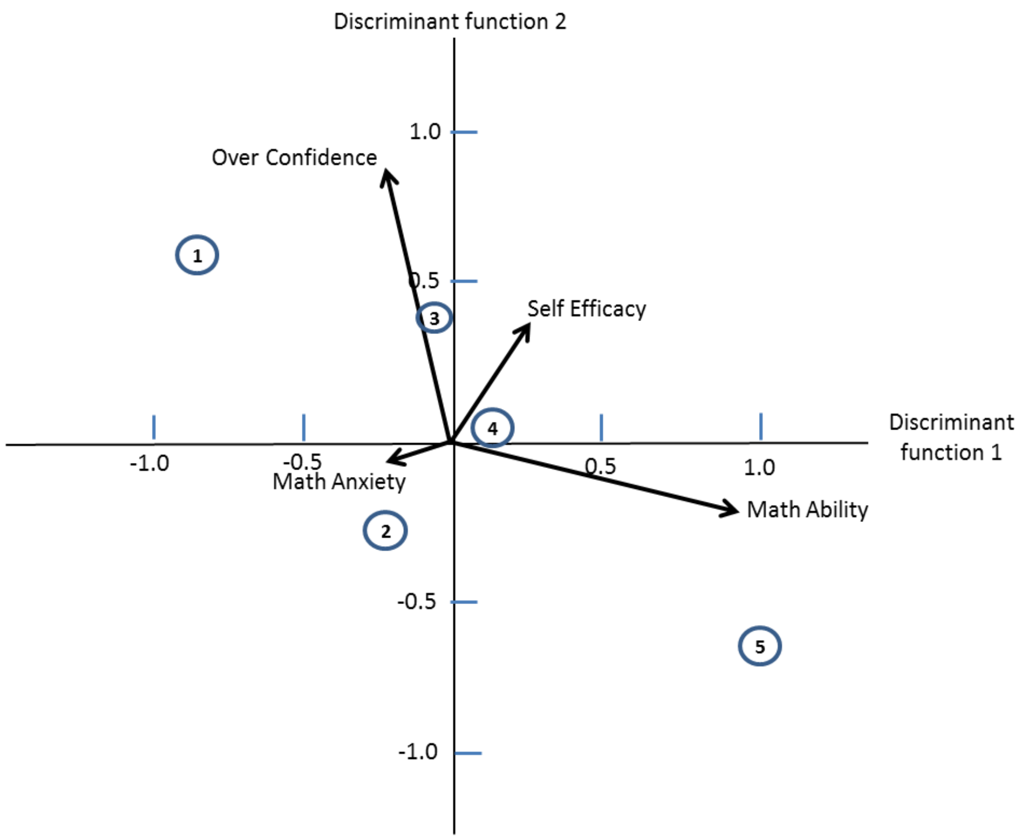
[1] Z = (correct classification rate – chance rate) / square root [(chance classification) (1 – chance classification rate) / group size].

The Z scores are significant at alpha = .05 for groups one, two and five. The discriminant model effectively classifies two performance groups; the at-risk students and the top performing students (at about triple the chance rate for each group). Performance category 2 students are correctly classified beyond chance while categories 3 and 4 are poorly classified.

Interpreting the Discriminant Functions

The primary purpose of the research was to develop and validate an approach to identify at-risk students. In addition to correctly classifying future students, the discriminant functions may also help to understand differences across the five performance categories. These potential insights may help the instructor to understand and guide the at-risk student. Figure 1 presents a plot of the performance group centroids and brand attributes vectors against the first two discriminant functions.

Plot of Performance Groups[1] and Attributes[2]



[1] Group centroids
[2] Rotated Attribute loadings

Figure 1: Plot of Performance Groups and Attributes

The first function is driven by math ability. The second function corresponds most closely to overconfidence. Analysis of variance was used to examine mean differences across the performance groups on the discriminant functions. Results are presented in Tables 7 and 8.

Table 7: ANOVA Results for Differences in Discriminant Functions Across Performance Groups

	F-Ratio	D.F.	P-Value
Function 1[1]	15.2	4,156	< .001
Function 2[1]	7.5	4,156	< .001

[1] The unstandardized canonical discriminant function coefficients were used to calculate the discriminant score.

Table 8: Means and Pairwise Comparisons of Discriminant Scores Across Performance Categories

	Performance Category 1	Performance Category 2	Performance Category 3	Performance Category 4	Performance Category 5	Significant Contrasts
Function 1[1]	-.75	-.20	-.11	.23	.98	1-2,3,4,5; 2-5; 3-5; 4-5
Function 2[1]	.48	-.27	.39	-.18	-.55	1-2,4,5; 2-3; 3-4,

[1] The unstandardized canonical discriminant function coefficients were used to calculate the discriminant score.

Based on pairwise comparisons, the at-risk student group is significantly lower than the other 4 groups on discriminant function 1. Likewise, group 5 is significantly higher than all other groups. For the second function, the at-risk group scores significantly higher than groups 2, 4 and 5. As a group the at-risk students can be characterized by low math ability and high overconfidence. The influence of self-efficacy is less straightforward. Self-efficacy loads about equally on both functions. For the at-risk student, the self-efficacy scores can be described as too high (leading to overconfidence) while for the top performing group self-efficacy is consistent with strong math ability. It has been suggested that the most functional efficacy beliefs are those that slightly exceed what one can actually achieve (Bandura, 1997). Similar to a finding by Pajares and Kranzler (1995), the level of confidence of the at-risk students is generally not matched by "reciprocal competence". In other words there needs to be a meaningful correspondence between confidence and ability. In the absence of requisite skills, desired performance is unlikely to occur (Siegel et al. 1985).

Further insights may also be available by examining the individual data for an identified at-risk student. As an example, among the nineteen at-risk students correctly classified in the current sample, there are six students who have extreme overconfidence scores (10 or greater compared to overall sample average of 4.9) and high self-efficacy perceptions (average score of 86.8; 12 points higher than the overall sample average) coupled with an average math ability score of 4.5 against an overall sample average of 8.4. These six students believe they can do the work (high self-efficacy) and are highly overconfident but are weak in math ability. Three of these six students have low math anxiety scores (one and one-half points lower than the overall sample average.) These students are at-risk but may be unaware of the risk, based on high self-efficacy perceptions, high overconfidence and low math anxiety. Among the same nineteen students are five who have low overconfidence scores (4 or lower; average score of 3.6; overall sample average of 4.9), low self-efficacy perceptions (average = 61; overall sample average = 74.7) and low math ability (average = 2.15). These students are also at-risk but most likely realize that risk, based on weak self-efficacy perceptions and low overconfidence.

Implementing the Approach

The early identification of at-risk students provides an important opportunity for the instructor to intervene. The authors therefore recommend gathering the relevant data at the start of the term. Consistent with the approach described in this research, the math ability and self-efficacy measures should be customized for the specific course in question. While it would be possible to conduct the research on-line, it is recommended that the data be collected during class, as a way to increase student effort and to generate a more realistic assessment of math ability, self-efficacy and math anxiety. The questionnaires requires about 50 minutes of class time. Following the administration of the questionnaires the class should be debriefed on the purpose of the data collection and students should be encouraged to meet with the instructor to discuss their results.

The at-risk students in this study are characterized by low math ability and high overconfidence. Given that these students can be identified at the start of the term, the instructor can focus on strengthening their math skills and helping them gain a more realistic assessment of their initial starting position.

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