Math SPIN News

Newsletter of the NADE Math SPIN

http://www.nademathspin.org October, 2008

From the co-chair

Math SPIN Folks,

Welcome back to the 2008-2009 school year! Susan McClory does all the real work as the SPIN chair, but she has asked me to introduce myself as the SPIN co-chair. I have been teaching full-time, with a few breaks for graduate school, since 1978. I have been with the developmental mathematics department at Salt Lake Community College since 1992. Besides teaching, my passions are writing (mostly 'math stuff'), fly-fishing, camping, backpacking, hiking, woodworking, gardening, etc. Running is my newest hobby. If you get a chance to see me run, I'm sure you will find it humorous. It's like watching an elephant trying to do 'the dance of the sugar plum fairy.'

Please read the articles in this newsletter and feel free to comment on them in the SPIN email discussion group. Laura's article challenges us to reexamine what we mean by a 'reasonable' answer. Alain challenges us to rethink the standard syllabi and to view arithmetic and algebra as a 'reasonable' way of expressing our understanding of the world. Robin's report has some marvelous analysis and is supported by the work published last year by the gang at Weber State University.

Let me close with one of the nuggets I've panned out over the years.
(I don't remember who originally shared this with me.)

Wemember Swope

- Wise (y's) over Wun
- $m = \dfrac{wise}{wun} = \dfrac{y_2 - y_1}{x_2 - x_1}$

Remember, every day we're helping folks improve their lives.

John Close

In This Issue

(If you are viewing this as a PDF file, click on the title or page number to jump to the article.)

Is It Reasonable? Helping Developmental Students Assess Their Work

Laura Bracken
Lewis-Clark State College, Lewiston, Idaho

When we say "check the answer to the (word) problem for reasonability and show your work," the student thinks "What is a reasonable answer? How do I show that my answer is reasonable? How many points is it worth?"

I require that my developmental students use a problem solving plan. Following the work of Polya, students must study the problem, identify a strategy, use the strategy, explain why the solution is reasonable, and report the solution. This is similar to what we see in many textbooks. What is different is that I require students to identify a problem solving strategy and a test of reasonability. The problem solving strategies include *one equation, several equations, proportion, formula, inequality, graph, function,* and *system of equations*. The tests of reasonability are *estimation, do it backwards, common sense, in-between, equal sides, units of measurement*, and *try a solution* (for inequalities.)

Requiring the problem solving plan helps students get started. Having them identify a problem solving strategy helps them think critically about the problem. Requiring a test of reasonability helps them develop the habit of reflecting on their answers.

If you want more information, contact me at bracken@lcsc.edu. ■

Math SPIN Officers:

Susan McClory, Chair	San Jose State University	mcclory@sjsu.edu
John Close, Co-Chair	Salt Lake Community College	jclose@mymail.slcc.edu
Roberta Lacefield, listserv moderator	Waycross College	rslace@waycross.edu
Daryl Stephens, webmaster	East Tennessee State University	stephen@etsu.edu

Math SPIN to Sponsor Session at NADE 2009

Editor's note: Every year at the NADE conference, each SPIN is offered the opportunity to present at least one sponsored session. The description below is the abstract of the session that is sponsored by the Math SPIN at Greensboro in 2009.

Which Bloomin' Math Course is Right? National Placement Practices

Members of the Math SPIN group present a bouquet of national survey results of testing and placement practices, cut scores, and curricular offerings for developmental courses through College Algebra at a colorful array of institutions, including two-year and four-year public and private colleges and universities. How well is everything working?

The goal is to inform the audience of the results of the survey and to create a dialogue about testing and placement issues. We will cover topics including curricular sequencing of developmental courses, testing and placement practices and instruments, cut scores, assessment of accuracy of placement as a predictor for success, pass rates, and rationale and outcomes of placement practices. We will also address the use of results of nationally standardized tests predictive of college success, such as ACT and SAT, as placement tools.

Our purpose is to determine what is happening and how well it is working by sampling selected institutions, which include a broad spectrum of various sizes and types from small private liberal arts institutions to large public comprehensive universities. Key math and/or enrollment administrators are invited to complete an on-line survey with specific groups of questions regarding practices and outcomes. The survey also gathers reflective assessments of the rationale for and satisfaction with current practices.

The group seeks to encourage a consensus among the session participants about successful practices based upon data harvested from the surveys.
We will present conclusions from existing literature on testing and placement outcomes and compare our results to the findings of other studies, from well-accepted research (Roueche & Roueche, 1999) to more recent and innovative approaches (Felder, Finney & Kirst, 2007).

This research has the potential to give rise to follow-up studies that will make more specific recommendations about best practices in testing and placement of math students for successful achievement of their requirements and goals.

References

Roueche, J. & Roueche, S. (1999). *High stakes, high performance: Making remedial education work*. Washington, D.C. Community College Press. (ERIC Document Reproduction Number ED454939).

Felder, J., Finney, J., & Kirst, M. (2007). *"Informed Self-Placement" at American River College: a CAS Study*. National Center Report #07-2. San Jose, CA:. The National Center for Public Policy and Higher Education.

Presenters:

K. D. Taylor, Professor, Utah Valley University, 801.863.8949, kd.taylor@uvu.edu
John Close, Professor, Salt Lake Community College, 801.957.3215, john.close@slcc.edu
Christina Gundlach, Assistant Professor, Eastern Connecticut State University, 860.465.4617, gundlachc@easternct.edu
Keith White, Assistant. Professor, Utah Valley University, 801.863.7261, keith.white@uvu.edu
Dr. Marva Lucas, Associate Professor, Middle Tennessee State University, 615.898.2568, mlucas@mtsu.edu
Dr. Victoria Wacek, Associate Professor, Ivy Tech Community College, 317.917.5701, vwacek@ivytech.edu
Michael Chandler, Assistant Director, University of New Hampshire, 603.641.4113, michael.chandler@unh.edu
Avijit Kar, Instructor, Abraham Baldwin Agricultural College, 800.733.3653 Ext. 5107, akar@abac.edu
Robert E. Moore, Director, Missouri Western State University, 816.274.4141, rmoore@missouriwestern.edu
Dr. Donna Saye, Assistant Professor, Georgia Southern University 912.478.0267 Ddbsaye@georgiasouthern.edu

---

(Editor's note: Many states and institutions are looking at redesigning their developmental math programs. Here is one such proposal.)

Transforming Course Design in Developmental Math
A Project of the California State University System
Susan McClory, San José State University

In the spring of 2007, the Chancellor's Office for the California State University System (CSU) embarked on a program of Transforming Course Design (TCD). The first step in the process was to identify courses of "high impact and low success" with the help of the Provosts on all 23 campuses of the CSU. After their recommendations were received, two courses were identified as the targets for course redesign. The two targets were Chemistry 1A and Developmental Math. Requests went out to all campuses to identify key personnel in each of these areas. Then, early in spring of 2008, the teams were formed.

The TCD team for Developmental Math was made up of five members of a design team (Brownson from Long Beach; Evans from Humboldt; Krebs from Los Angeles; Moore from Stanislaus; and myself from San Jose) plus ten members of a review team representing eight additional CSU campuses. In order to orient the teams in the process of course redesign, several members of both the Chemistry and Developmental Math design teams attended the annual conference for the National Center for Academic Transformation (NCAT) in March. Working with Tom Carey, a consultant hired by the CSU Chancellor's Office, and Jeff Gold from the Chancellor's Office, the teams embarked on their charge.

The purpose of a course redesign is to improve student outcomes while reducing costs. Our first steps were twofold. While gathering data from each CSU campus to determine best practices, the team also began developing "personas" that characterized at risk students in Developmental Math courses. The personas helped the team identify characteristics leading to course failure that could be addressed by a redesign of the courses. This process exposed the fact that the demographics for the various campuses were very different and the needs for each campus would therefore be different.

As the team worked through the spring semester, with weekly conference call meetings and two face-to-face meetings, certain topics began to emerge as dominant themes in the work. First, in order to best serve students' needs, the need for a good diagnostic placement test is necessary. Currently, the CSU uses its own placement test called the Entry Level Math exam (ELM). It is scored by ETS and provides campuses with a numerical score on a scale of 10 – 80. There are no sub scores and no diagnostic information available from this test. Part of the final report suggests that the ELM would need to be changed in order to provide accurate placement information.

The second focus of the redesign team was on alternative instructional strategies. The team looked at the six models for course redesign as described by NCAT: supplemental; replacement; emporium; fully online; buffet; and the linked workshop model (see http://www.thencat.org/PlanRes/R2R_ModCrsRed.htm for a description of each). The focus ended up being on mastery learning, technology, supplemental instruction, and different pathways for different cohorts of students.

There is also a section in the final report on efficiency improvements and cost savings that outlines how the various redesign plans could affect not only the cost, but the number of sections required as well as how to move students through developmental math more quickly. A variety of summer and "quick start" programs were investigated and a summary of best practices is included in the report.

Finally, the team members each submitted a redesign proposal for their campus. There has been a promise of ongoing support for redesign projects, but the budget being what it is in California, funding levels are somewhat uncertain at this time. But, there will be a statewide conference on October 30 and 31 sponsored by the CSU Chancellor's Office at which many of the TCD team will be presenting their findings. The meeting will bring together representatives of all 23 CSU campuses as well as representatives from the California Community College system for a sharing of initiatives and best practices.

To view the full report of the Developmental Math Redesign Team and for a peek into the process, go to: http://groups.google.com/group/csu-transform-dev-math-teams.

A Model-Theoretic Approach to Developmental Mathematics

Alain Schremmer
Community College of Philadelphia

As I have frequently alluded to on the MathSPIN list, I am engaged in a massive project meant to improve the abysmal pass-rate in Calculus I for students starting in arithmetic. At CCP, it is less than one quarter of one percent (0.24%). For very many years now, I have seen this and then that approach as the one sure way to solve the problem but I don't have a feeling that the problem is any way closer to be solved. (By the way, I mention Calculus I only because this is where my own interests lie but I doubt very much that the pass-rate is any better at any other equivalent level. In any case, this then begs the question as to whether developmental students somewhat "inferior" and therefore naturally doomed or that they are so far behind that there isn't really much that we can do for them or are there other reasons, such as maybe that we as developmental teachers are failing them?)

I believe that the source of this deplorable situation is the "topics approach" because it essentially prevents any buildup and any transfer. By the way, an even worse version of the "topics approach" is the "problem approach" and, as it happens, a piece of research has just appeared which however is a bit misleading inasmuch as it keeps talking about "examples" but really deals with "problems." See http://www.nytimes.com/2008/04/25/science/25math.html?_r=1&oref=slogin and http://www.eurekalert.org/pub_releases/2008-04/osu-ced042108.php.

Beyond that, though, I believe that there are two possible views of—or at least two possible syllabi for — a developmental course:

- A comprehensive range of topics, methods, mathematical facts, etc that will be necessary/useful to the students in their further mathematical studies.
- The systematic development on a few topics of an ability in mathematics to help the students "cope" in their further studies—not necessarily just mathematical.

The approach that I am taking in the project is along the second view and, more precisely, it is a model-theoretic one. (Nothing to do with modeling). To give a rough idea of what a model-theoretic approach is, let me quote from the very first paragraph of the text I recently uploaded on http://www.freemathtexts.org/RBAtext.html .

> To put it as briefly as possible, Arithmetic and Algebra are both about developing procedures to figure out on paper the result of real-

> world processes without having to go through the real-world processes themselves. To make this a bit clearer, here are two examples from Arithmetic the Algebra counterpart of which we will deal with in Part III of this book.

and, a few pages later,

> As a matter of fact, this is most likely how, several thousands of years ago, Arithmetic, got started when, one may imagine, Sumerian merchants, faced with the problem of accounting for more goods in the warehouse and/or money in the safe than they could handle directly, decided to have both the goods and the money represented by various scratches on clay tablets so that they could see from these scratches the situation their business was in without the inconvenience of having to go to the warehouse and/or to open the safe.

Another issue that I believe is not given enough attention concerns matters of language. To shrink the level of a textbook to an asinine level is insulting to the students as well as counterproductive. In the project, I have given a great deal of attention to matters of language and that in fact seems to contribute to a smoother conceptual flow and to helping the students focusing on, and coming to grasp with, the issues.

As I think I already mentioned on the spin list, this emphasis on the development of a language seems to intrigue some people in the English department and, this coming Fall, there might be a "link" in which the reading material in the English developmental course will be the text used in the Math developmental course from which the above is excerpted.

As for whether the whole thing "works," I think that it does, whatever that may mean, but I have only circumstantial evidence and no hard systematic data. ■

Your Math SPIN website has 17 years of past newsletter issues. Check it out at www.nademathspin.org.

Would you like to join the Math SPIN e-mail discussion group? Directions are on the website also or in newsletter from the past four years.

Math SPIN News
Send submissions to Susan McClory, Chair, at mcclory@math.sjsu.edu.
Issue Editor: Daryl Stephens, East Tennessee State University (stephen@etsu.edu)

Analysis of Developmental Math Intervention Initiative

San Juan College, Spring 2007

Dr. Robin Riordan

Introduction

Five hundred six students, enrolled in two developmental math courses, were followed during spring semester 2007. The two courses were Pre Algebra, hereafter referred to as Math 095, and Introductory Algebra, hereafter referred to as Math 096. One hundred and nine students were enrolled in Math 095 and three hundred and ninety seven in Math 096.

The purpose of this investigation was to evaluate the effectiveness of making personal contact with students who were experiencing problems with attendance, tests, and quizzes as a means of improving their success rates. Each week class rosters were distributed to instructors in order to facilitate identifying and reporting students experiencing problems. An attempt was made to contact the identified students when rosters were returned. Dates of attempted and successful contacts were recorded in a database.

Additional variables were considered worthy of consideration as explanatory factors for the success in developmental math. These factors were: gender, race, age, and years elapsed since last math course. Since the data are categorical, a log – linear analysis was selected as the appropriate statistical method for isolating potentially relevant effects. Each effect was treated as a dichotomous variable in an effort to prevent the expected frequencies from falling below five.

Not all classes participated in the intervention program and are treated as a control group in the analysis of the intervention portion of this study.

Data Gathering Procedure

Tim Schroeder, Senior Director for Student Success, and Robin Riordan, Mathematics Learning Specialist, met with members of the math faculty at the beginning of Spring Semester 2007 to share the purpose of the student intervention initiative. A reporting format was adopted from Achieving the Dream. The categories used for identifying student problems are:

Attendance	Missed homework	Failed quizzes
Failed exams	Difficulty with concepts	Non-participation

Although class rosters were distributed to math 095 and 096 instructors they were not required to return them and if they chose to return them they could do so at a time of their choosing. Upon receiving alerts from instructors students were contacted by home phone, cell phone, or email, depending on their preferred method of contact. Data were recorded in a spreadsheet using the following format.

Name	Course	Instructor	Problem Code	Attempted Contact Dates	Contact Date	Results

Additional columns were inserted to include demographic data. These data were: gender, age, race, major, years elapsed since taking a math course, number of alerts received from instructors, number of times contacted, grade received, and time receiving tutor assistance.

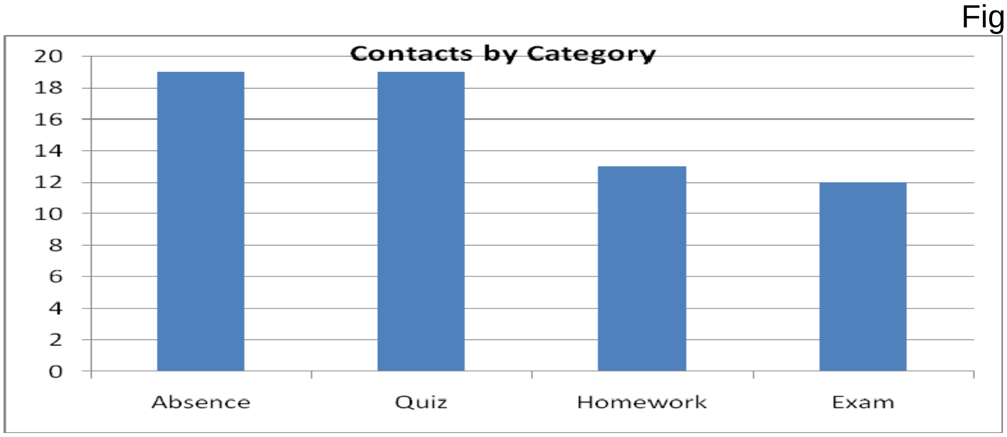
Demographics and Data Coding

There are a large number of factors that might influence the successful completion of a math course. Additionally, one must consider the possible interaction among these variables. Since we are interested in the effect of contacting students on their success, both of which are nominal variables, we selected a non parametric analysis methodology. Furthermore, the other factors of interest lend themselves to nominal coding.

Contacts

For this study contacts are treated within the context of the experimental group. Within the categorical variable, participant, those students enrolled in a class which participated in the intervention program are coded 1 and those enrolled in a non-participating group are coded 0. This coding will avoid inadequate observed and expected cell frequencies while maintaining experimental integrity. The distribution of contacts by problem code is represented in Figure 1.

Figure 1

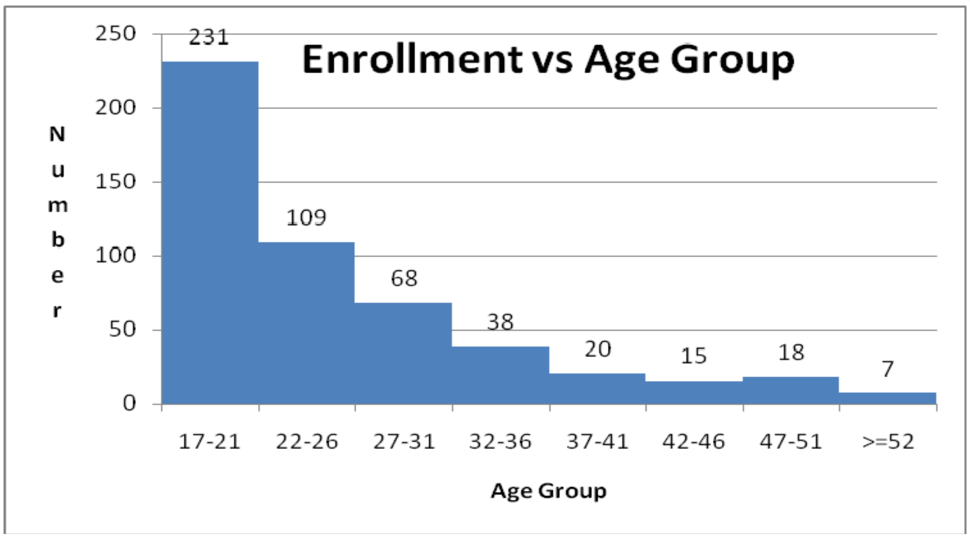


There are a total of sixty three contacts represented in the bar graph. Of these, forty seven represent unique students. The remainder reflects multiple student contacts. This is out of a total enrollment of 506 students.

Age

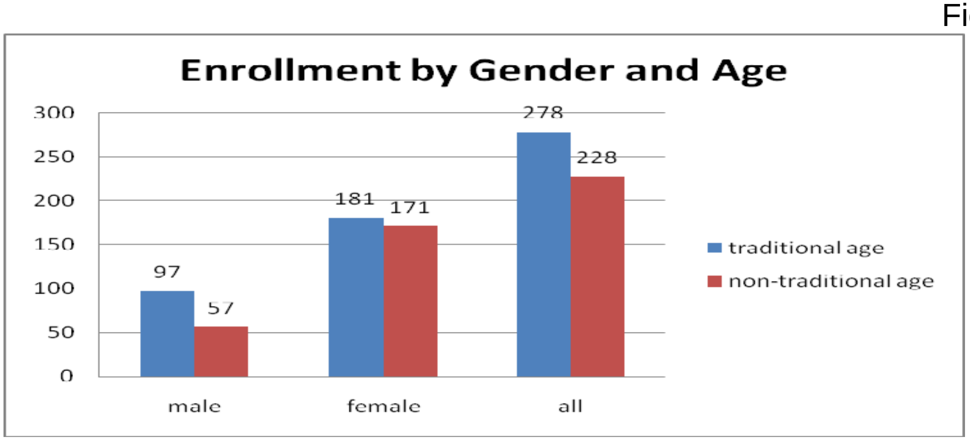
The ages of students enrolled in developmental math spans forty years, ranging from seventeen to fifty seven years. Many studies have split this into two age groups. Students of a traditional university age, seventeen through twenty three, are placed into a traditional group while the remaining students are placed into a non-traditional category. A number of confounding variables may be subsumed within the age factor. Among these might be: locus of control, life experience, identity formation, motivation, career orientation, child care issues, time management skills, and financial stability. The age distribution of students enrolled in developmental math is in diagram 2.

Figure 2



Since Community Colleges have a history of non-traditional enrollment it is illuminating to examine the distribution of enrollment as a function of gender and age. There is a distinct possibility that these factors could be interactive effects in a log-linear model. Even if they are not significant in the omnibus model a univariate analysis may provide some insights for future considerations. A distribution is found in figure 3.

Figure 3



Race/Ethnicity

Five ethnic groups are enrolled at San Juan College: Caucasian, African American, Native American, Hispanic, and Asian. The distribution of enrollment by race and ethnicity is in table 1.

Table 1

	Caucasian	African Am	Native Am	Hispanic	Asian	Unknown
Male	48	2	88	7	3	11
Female	112	2	169	40	3	21
Combined	160	4	257	47	6	32

Clearly, the African American and Asian populations are too small to be statistically significant. Since Community Colleges are generally concerned with effects observed between the dominant culture and under-represented cultures, it is deemed appropriate to collapse these categories into two groups.

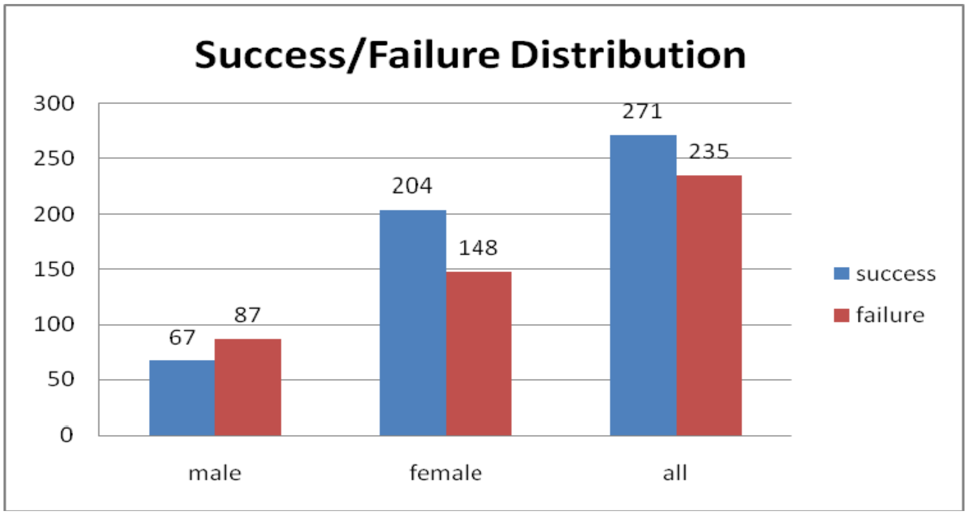
Years Since Last Math Course (Lapse time)

Given the large dispersion of the ages of the students enrolled in developmental math, it comes as no surprise that there is a correspondingly large dispersion in the years elapsed since the last math course taken. The range observed is zero to thirty four years. The median age is one year. There is a very distinctive break between one year and over one year. Three hundred and seven students fall within the less than two years lapse group and one hundred and ninety nine are in the two or more year's lapse group. Given the exponential rate of loss of math skills with time, a dichotomous code was created for which one group contained students with a zero to one year lapse since their last math course. The other group contained all students with two or more years since being enrolled in math. It should be noted that the lapse factor may reflect effects of age as well as absence from exposure to math. This may be a very confounded factor.

Success

Success is defined as a grade of A, B, or C. Failures are defined as D, F, withdraws, and incomplete. Success is the dependent variable in logit analysis, which is a general linear model at the nominal level. Success is just a factor, among other factors, within a log-linear analysis. The distribution of success and failure across gender and age are found in figure 4.

Figure 4



Analysis

There are several reasons for selecting a log-linear analysis of the data. The factor of concern is student success as opposed to failure. This is a nominal (categorical) variable. If the variable were of a metric nature we could apply an analysis of variance. Furthermore, we must avoid using multiple Chi-Square analyses because of the propagation of the error inherent in multiple univariate analyses. The experiment wide error rate with this approach is:
$EW_{\alpha}=1 - (1 - \alpha)^{c}$ where α = significance and c = the number of multiple tests. Additionally, one does not know which factors are interacting with a multi-Chi-Square approach.
Three assumptions are made for a log-linear analysis:

1. Observed cell frequencies are adequate
2. Small cell frequencies probably indicate either an inadequate sample or rare cases
3. To preserve statistical power, all 2-way expected frequencies should be greater than 1 and not more than 20% should be less than 5

Hierarchical Log-Linear Analysis

The factors considered in this model are: gender, race/ethnicity, age, participation, and success. As mentioned before, all variables are nominal and dichotomous. The analysis will fit a perfect expected model (saturated) to the observed data. This can be thought of a combining the observed cell frequencies in a Chi-Square contingency table in a manner that produced expected frequencies to match observed frequencies. In this way we produce a model which would represent complete factor independence. Thus, $X^2 = 0$ and $p = 1$. Actually, in a log-linear analysis, the maximum-likelihood-ratio, [Eq. 1] $G^2 = 2\sum\left(f_{ij}\right)\left(\frac{f_{ij}}{F_{ij}}\right)$ where f_{ij} are observed cell frequencies and F_{ij} are expected cell frequencies. For large N, G^2 approaches X^2.

We are given the variables:

Gender (G)

Race/Ethnicity (R)

Age (A)

Participation (P)

Success (S)

The possible significant relationships are:

Table 2

None	G × R	G × A
G × P	G × S	R × A
R × P	R × S	A × P
A × S	P × S	G × R × A
G × R × P	G × R × S	G × A × P
G × A × S	G × P × S	R × A × P
R × A × S	R × P × S	A × P × S
G × R × A × P	G × R × A × S	G × R × P × S
R × A × P × S	G × R × P × S	G × R × A × P × S

We construct a log linear model that will reproduce the logarithms in each cell. For the sake of clarity and brevity, let's assume that we have only three effects in the model. The resulting log-linear model would be:

$\ln\left(n_{ijk}\right) = \mu + \lambda_i^G + \lambda_j^{\,S} + \lambda_k^{\,A} + \lambda_{ij}^{\,GS} + \lambda_{ik}^{GA} + \lambda_{jk}^{SA} + \lambda_{ijk}^{GSA}$ where

$\ln(n_{ij})$ = Logarithm of the cell frequency of cell ij

μ = A constant: the mean logarithm across all cells

λ_i^G = The increase or decrease from μ due to gender

λ_j^S = The increase or decrease from μ due to success

$\lambda_k^A =$ The increase or decrease from μ due to age

λ_{ij}^{GS} = The interaction term: the increase or decrease from μ due to a particular combination of gender and success (G × S).

$\lambda_{ik}^{GA} =$ The interaction term: the increase or decrease from μ due to a particular combination of gender and age.

$\lambda_{jk}^{SA} =$ The interaction term: the increase or decrease from μ due to a particular combination of success and age.

$\lambda_{ijk}^{GSA} =$ The interaction term: the increase or decrease from μ due to a particular combination of gender, success, and age.

The model for a five variable model is much more complicated considering all the combination possible.

During the log-linear analysis the impact of the various effects are measured by removing terms from the saturated model and see if there is a significant change. For our model above one might remove λ_{ij}^{SA} and estimate the expected frequencies using this unsaturated log-linear model. If the expected frequencies from this unsaturated model are significantly different than the observed, then that effect is significant. The parameters for the unsaturated model are estimated by an iterative proportional-fitting algorithm. The ultimate objective is to identify the most parsimonious model which still achieves a satisfactory level of goodness of fit. In other words, we test to see if a restricted model does not differ significantly from the saturated model. If there are no significant differences, then one can conclude that the effects dropped from the saturated model were not needed to explain the observed distribution of data.
After each effect is removed the maximum-likelihood-ratio is calculated using Eq 1. For large G^2 the difference between observed and expected cell frequencies is large and corresponds to a significant effect.

The final model produced by the hierarchical log-linear analysis contained the following effects:
Race × Age × Participation × Success
Gender × Race × Age
Gender × Participation
Gender × Success
The maximum likelihood ratio = 3.12956 DF = 10 P = .978
This is quite good considering a saturated model yields P = 1.
Table 3 contains the observed frequencies, expected frequencies, and residuals for this model.
The codes for the variables are:

Gender: male = 1, female = 2
Race/ethnicity: 1 = dominant culture, 2 = non- dominant
Age: 1 = 17 – 23, 2 = over 23
Participation: 0 = no, 1 = yes
Success: 0 = no, 1 = yes

Table 3
Hierarchical Log-Linear Output for Best Fit Model

Factor	Code	OBS	EXP	Residual	Std Resid
GENDER	1				
RACE	1				
AGE	1				
PARTICIP	0				
SUCCESS	0	6	6	0.01	0
SUCCESS	1	2	3.2	-1.23	-0.69

PARTICIP	1				
SUCCESS	0	9	8.2	0.82	0.29
SUCCESS	1	4	3.6	0.4	0.21
AGE	2				
PARTICIP	0				
SUCCESS	0	6	4.9	1.1	0.5
SUCCESS	1	9	9.3	-0.34	-0.11
PARTICIP	1				
SUCCESS	0	2	2.7	-0.67	-0.41
SUCCESS	1	8	8.1	-0.09	-0.03
RACE	2				
AGE	1				
PARTICIP	0				
SUCCESS	0	20	22.1	-2.11	-0.45
SUCCESS	1	17	14.6	2.35	0.61
PARTICIP	1				
SUCCESS	0	25	24.6	0.44	0.09
SUCCESS	1	14	14.7	-0.69	-0.18
AGE	2				
PARTICIP	0				
SUCCESS	0	9	9.5	-0.54	-0.17
SUCCESS	1	9	8.2	0.76	0.27
PARTICIP	1				
SUCCESS	0	10	9.1	0.94	0.31
SUCCESS	1	4	5.2	-1.17	-0.51
GENDER	2				
RACE	1				
AGE	1				
PARTICIP	0				
SUCCESS	0	11	11	0	0
SUCCESS	1	12	10.8	1.23	0.37
PARTICIP	1				
SUCCESS	0	16	16.8	-0.81	-0.2
SUCCESS	1	13	13.4	-0.41	-0.11
AGE	2				
PARTICIP	0				
SUCCESS	0	6	7.1	-1.12	-0.42
SUCCESS	1	25	24.7	0.35	0.07
PARTICIP	1				
SUCCESS	0	5	4.3	0.66	0.32
SUCCESS	1	24	23.9	0.1	0.02

RACE	2				
AGE	1				
PARTICIP	0				
SUCCESS	0	29	26.9	2.1	0.41
SUCCESS	1	30	32.3	-2.35	-0.41
PARTICIP	1				
SUCCESS	0	33	33.4	-0.44	-0.08
SUCCESS	1	37	36.3	0.69	0.11
AGE	2				
PARTICIP	0				
SUCCESS	0	24	23.5	0.55	0.11
SUCCESS	1	36	36.8	-0.77	-0.13
PARTICIP	1				
SUCCESS	0	24	24.9	-0.94	-0.19
SUCCESS	1	27	25.8	1.16	0.23

Goodness-of-fit test statistics

Likelihood ratio chi square =	3.12956	DF = 10	P = .978
Pearson chi square =	3.05276	DF = 10	P = .980

The residuals in the table are calculated from:

$R = (O_f - E_f)$ where R = residual

O_f = observed frequency

E_f = expected frequency

The standardized residuals are calculated from:

$$Z = \frac{R}{\sqrt{E_f}}$$ where Z = standardized residual

R = residual

E_f = expected frequency

Standardized residuals $Z \geq \pm 1.96$ indicate that the model is a bad fit to the observed frequencies. It is worth noting that the standardized residuals in the data table are well below 1.96.

General Log-Linear Model

Now that the most parsimonious model has been identified through the Hierarchical Log-Linear Analysis, it can be fitted into a general log-linear model. This type of model is very much like a discriminant analysis for metric independent variables and nominal dependent variables. Log-linear analysis is sometimes referred to as linear probability, and is a combination of multiple regression and discriminant analysis. It is distinguished from multiple regression inasmuch the dependent variable is non-metric. A major conceptual and analytical change that occurs in this model, as opposed to the hierarchical log-linear model, is we now identify one of the variables as a dependent variable. Since we are concerned with student success in developmental math we will adopt success as the dependent variable. Thus, the logit function is written in the form of a general linear model.

$$Y_j = \beta_0 + \sum \beta_i f(X_j)$$

Where $f(X)$ represents some mathematical function of X and β represent coefficients which are estimated.

The design for our multinomial logit which involves participation is:
Constant + Success + Success x Age + Success x Participation + Success x Race. Since we are interested in success and participation we ignore effects which do not include these factors. Each main effect is accounted for and as many interactive terms that are needed to arrive at a satisfactory fit. One should avoid over-fitting the model with excessive interactions inasmuch additional noise will be added along with the true effects. There is a separate constant term for each combination of levels of the independent factors. Since the dependent variable in this study is dichotomous logistic regression is a good choice to avoid possible deviations from normality.

Table 4

Residual Output from General Log-Linear Analysis

Factor	Value	Resid.	Adj. Resid.	Deviate
RACE	1			
AGE	1			
PARTICIP	0			
SUCCESS	0	3.23	1.45	2.67
SUCCESS	1	-3.23	-1.45	-2.41
PARTICIP	1			
SUCCESS	0	4.92	2.04	3.31
SUCCESS	1	-4.92	-2.04	-2.94
AGE	2			
PARTICIP	0			
SUCCESS	0	-2.07	-0.87	-1.95
SUCCESS	1	2.07	0.87	2.07
PARTICIP	1			
SUCCESS	0	-6.08	-2.63	-2.96
SUCCESS	1	6.08	2.63	3.67
RACE	2			
AGE	1			
PARTICIP	0			
SUCCESS	0	-3.22	-1.1	-2.5
SUCCESS	1	3.22	1.1	2.58

PARTICIP	1			
SUCCESS	0	-4.93	-1.62	-3.08
SUCCESS	1	4.93	1.62	3.22
AGE	2			
PARTICIP	0			
SUCCESS	0	2.06	0.73	2.06
SUCCESS	1	-2.06	-0.73	-2.01
PARTICIP	1			
SUCCESS	0	6.09	2.23	3.66
SUCCESS	1	-6.09	-2.23	-3.33

Goodness-of-fit Statistics

	Chi-Square	DF	Sig.
Likelihood Ratio	12.7172	4	.0127
Pearson	12.2662	4	.0155

Analysis of Dispersion

Source of Dispersion	Entropy	Concentration	DF
Due to Model	8.6746	8.5225	3
Due to Residual	340.78	243.1969	502
Total	349.45	251.7194	505

Measures of Association

Entropy = .0248

Concentration = .0339

The maximum likelihood ratio p = .0127 indicates a significant departure from factor independence. We must conclude that success is associated with the effects in the model but the effect size, reflected by the concentration reflects a small to moderate association. It is also noteworthy that the entropy is very low, indicating a low dispersion association.

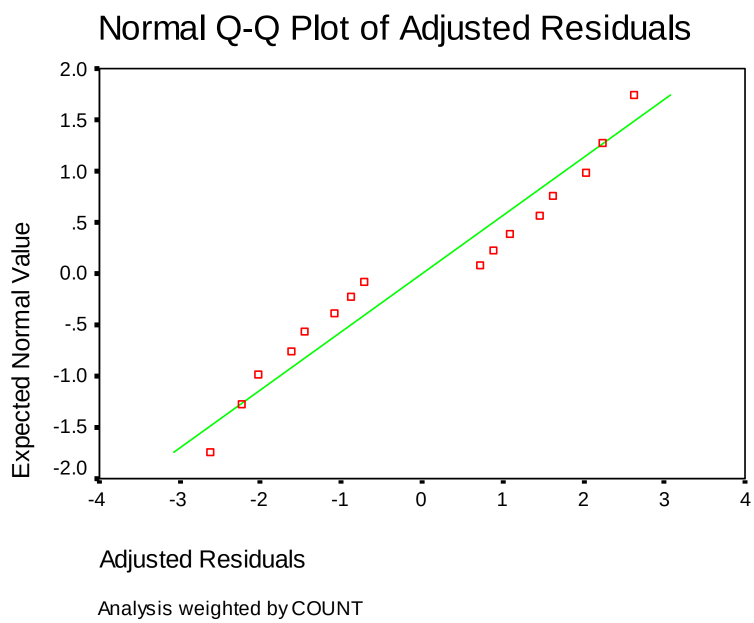
The contribution of each cell to the overall model can be discerned from the deviates found in table 4. The deviates approximate a z statistic.

The Freeman-Tukey deviate is expressed as

$$D_{ij} = \sqrt{f_{ij}} + \sqrt{f_{ij}+1} - \sqrt{4F_{ij}+1}$$

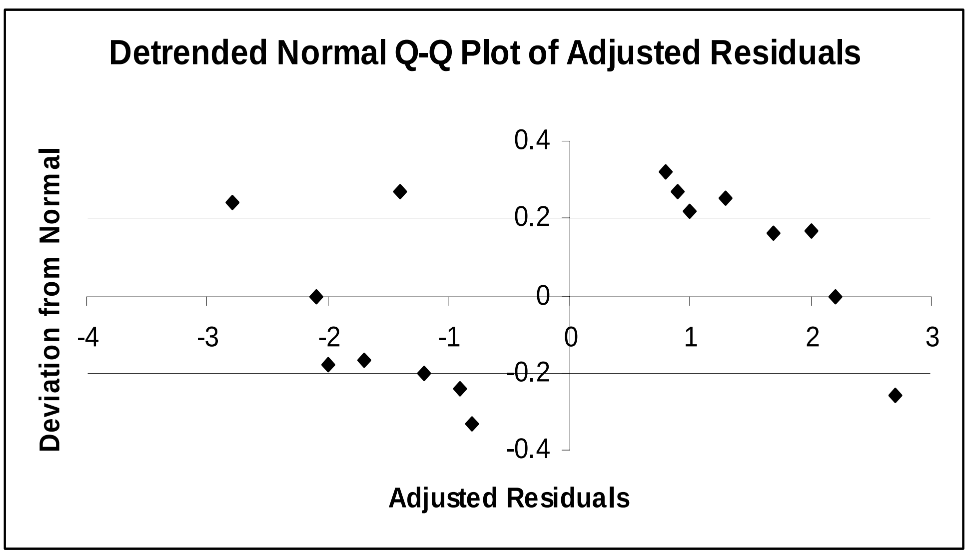
$\sqrt{f_{ij}} + \sqrt{f_{ij}+1}$ is referred to as the variance stabilization transformation which is distributed approximately as a normal distribution with a mean of $\sqrt{4F_{ij}+1}$. A minimum residual distance of ± 2.00 is used as a rough indicator of significance at the .05 level. The sign of the deviates indicate the directionality. Almost without exception all effect combinations are significant. This conformity to normal distribution behavior is examined in figures 5 and 6.

Figure 5



The diagonal line defines a perfectly fitted Gaussian. The plotted residuals follow this line very nicely with minor kurtosis. This is expected from a well fitted model.

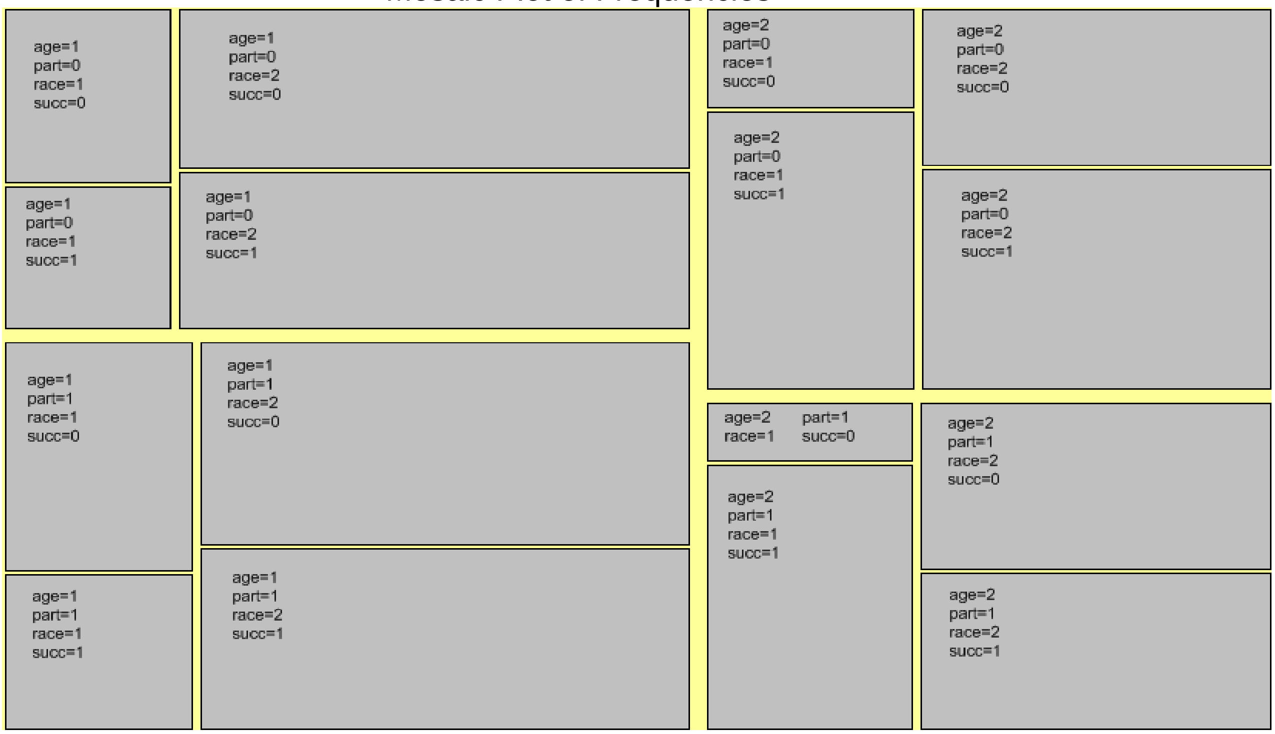
Figure 6

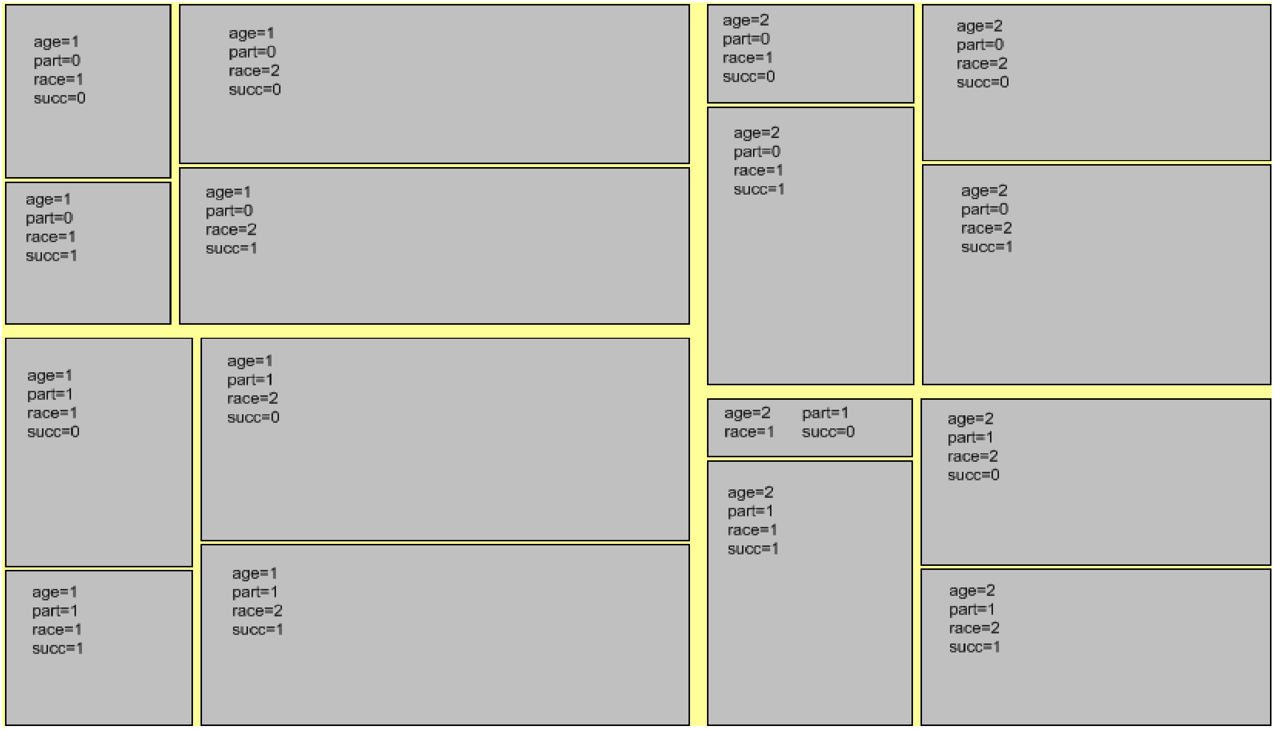


As one can see from the graph of the detrended normal Q-Q plot of adjusted residuals, the distribution is random, with a coefficient of determination $R^2 = .041$. This indicates a well fitted model. For the sake of visualization a frequency mosaic of the frequencies in each cell of the model is provided in figure 7.

Figure 7

Mosaic Plot of Frequencies





Following are post hoc Chi Square tabulations.

Gender*Success Crosstabulation

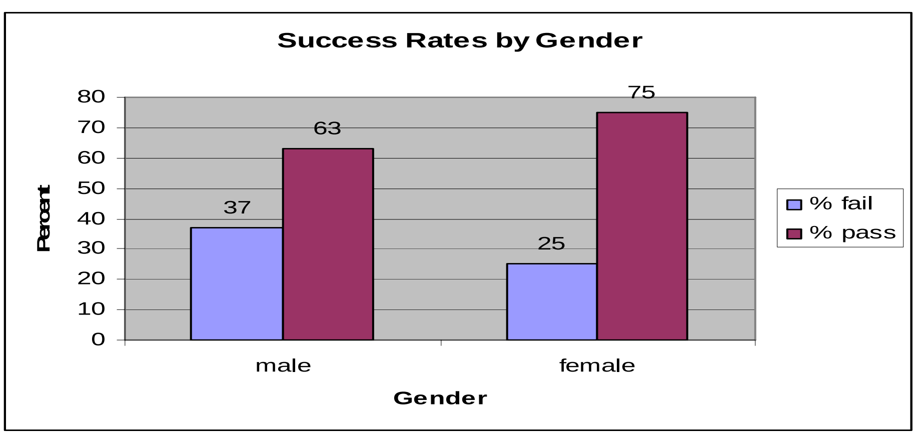
			Outcome		
			Failed	Succeed	Total
Gender	Male	Observed	87	67	154
		Expected	71.5	82.5	154
		% within success	37.0%	24.7%	30.4%
	Female	Observed	148	204	352
		Expected	163.5	188.5	352
		% within success	63.0%	73.3%	69.6%

Chi-Square Test

	Value	df	Asymptotic Sig 2 side
Pearson Chi-Sq	8.991	1	
Likelihood Ratio	8.988	1	
Fisher's Exact Test			0.002

Directional Measurement Gender Dependent
Goodman-Kruskal Tau = 0.003

The Goodman and Kruskal tau has symbol τ , the Greek letter tau. τ is obtained by using the principle of proportional reduction in error. Like λ this is a directional measure of association, with different values depending on whether rows or columns of a cross-classification table are dependent. τ has limits of zero (no association) and 1 (complete or perfect association).

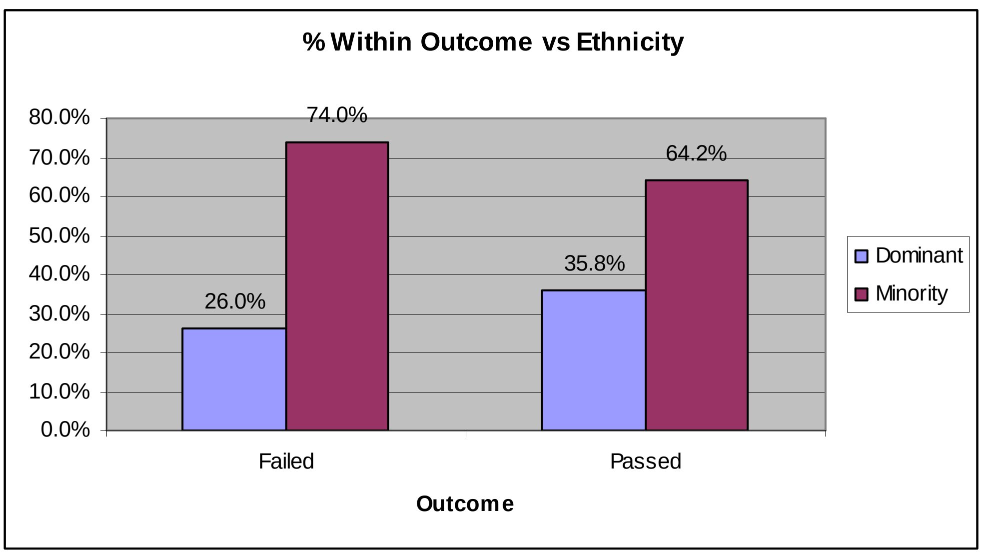


Ethnicity*Success Crosstabulation

			Outcome		
			Failed	Succeed	Total
Ethnicity	Dominant	Observed	61	97	158
		Expected	73.4	84.6	158
		% within success	26.0%	35.8%	31.2%
	Minority	Observed	174	174	348
		Expected	161.6	186.4	384
		% within success	74.0%	64.2%	68.8%

	Value	df	Asymptotic Sig 2 side
Pearson Chi-Sq	5.67	1	0.017
Likelihood Ratio	5.712	1	0.017
Fisher's Exact Test			0.021

Directional Measurement Ethnic Dependent
Goodman-Kruskal Tau = 0.017



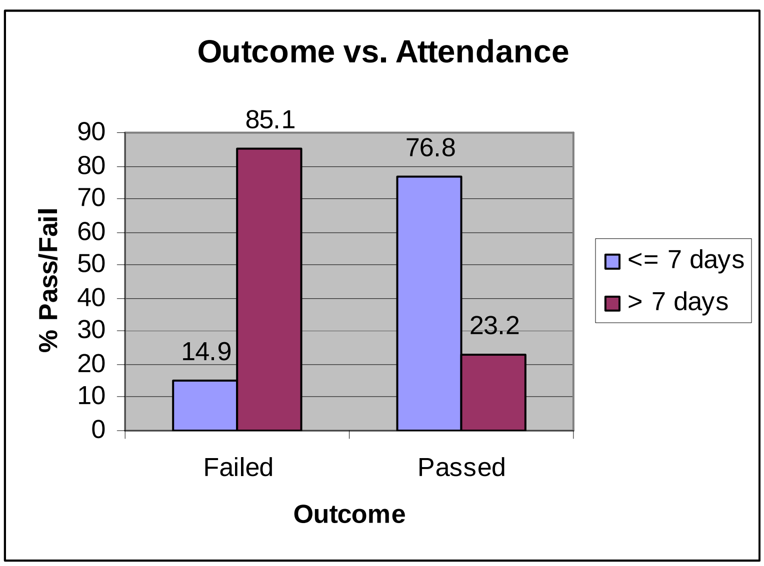
Absence*Success Crosstabulation

			Outcome		
			Failed	Succeed	Total
Absence	<=7days	Observed	7	63	70
		Expected	25.5	44.5	70
		% within success	14.9%	76.8%	54.3%
	>7days	Observed	40	19	70
		Expected	21.5	37.5	59.9
		% within success	85.1%	23.2%	47.7%

Chi-Square Test

	Value	df	Asymptotic Sig 2 side
Pearson Chi-Sq	46.17	1	0
Likelihood Ratio	49.55	1	0
Fisher's Exact Test			0

Directional Measurement Ethnic Dependent
Goodman-Kruskal Tau = 0.00



Attendance-success was the second model that emerged from the hierarchical log-linear analysis.

These chi-square analyses reflect the significance of gender, ethnicity, and attendance as main effects on success.

Conclusion

During the Spring Semester 2007 San Juan College implemented an intervention program for students enrolled in developmental math. The intervention strategy consisted of identification of students who were at risk as a result of poor attendance and poor performance on tests and assignments. The names of these students were passed on to the student success center through which contacts with these students was made. Students were invited to come to the student success center's tutoring service and/or come in for a consultation. Contacts with students were recorded. Approximately 50% of the developmental math classes participated in the intervention program; the other 50% were used as a control group. A database developed and maintained by Gerald Williams, Associate Professor of Mathematics, was joined with the contact records to form the overall database for the analysis. Attendance analysis was restricted to students enrolled in the cohort groups of math 095. All other analysis used data combined from math 095 and 096.

Hierarchical Log-Linear analysis was selected as the method of analysis for this multi-nominal data set. The nominal variables included: gender, ethnicity, age class, participation, and success. Through a method of backward eliminate two significant models were identified: gender* success and age*participation*ethnicity*success. Since gender*success is a simple 2 by 2 model it was considered in the post hoc analysis and demonstrated to be significant. A logit analysis was conducted on the multiple-model and, through an analysis of residuals, all interactions were found to be significant. Thus, we are able to conclude that within the context of a four way interaction the intervention protocol does affect the outcome of student success. It must be noted that the effect size in this experiment is very low, approximately 0.01. Thus, although statistical significance is demonstrated, impact is questionable.

Limitations

This study is based on a quasi-experimental design. There was no random selection of experimental and control groups. Participating and non-participating classes were self-selected. Furthermore, only forty-seven unique students were contacted in the experimental group. If we assume an equal partition between experimental and control groups, this would represent forty-seven students out of two hundred fifty-three students. With this small sample size we should be concerned with the effect size. Given a historical failure rate of 50% we would hope for a larger sample size. The intervention program shows promise but a strict experimental design should be imposed and greater participation encouraged. ■