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A Concurrent Support Course for Intermediate Algebra

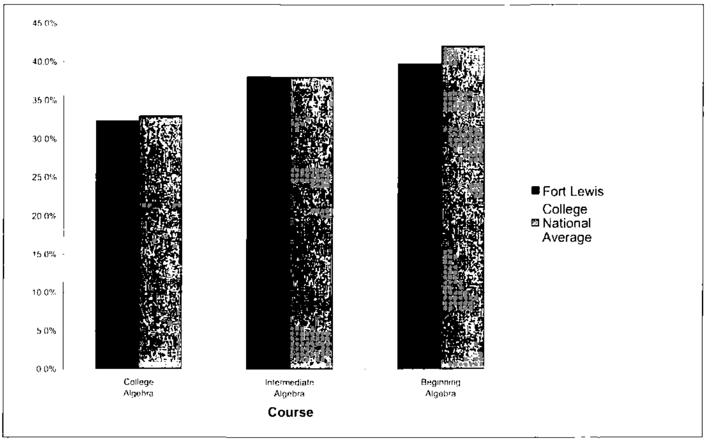
Abstract

This article summarizes the creation and implementation of a concurrent support class for TRS 92 – Intermediate Algebra, a developmental mathematics course at Fort Lewis College in Durango, Colorado. The concurrent course outlined in this article demonstrates a statistically significant increase in student success rates since its inception. Specifically, students successfully completing the concurrent support class have had a success rate of approximately 82%, while all other students have had an approximate 63% success rate. In Spring 2007, the support course was piloted in a randomized control, experimental design. As measured by Cohen's d, the pilot course resulted in overall effect size 0.43, a moderately strong effect size for behavioral data.

Introduction

Nationally, Intermediate Algebra is second only to Beginning Algebra as having the highest student failure rate in developmental mathematics courses at two-year and four-year schools (Adelman, 2004, p. 665).

Fort Lewis College is consistent with national failure rates for developmental mathematics courses. It is thus reasonable to hypothesize that any benefits realized by this research at Fort Lewis College could also be realized at other similar institutions of higher education. A comparison to Fort Lewis College and national success rates is shown below:



The basic approach taken by this research to improve student success rates in Intermediate Algebra involved the following steps:

1. Identifying the students in Intermediate Algebra who are not likely to succeed.
2. Using the salient variables used to identify the students in step 1 to create a support course that could address specifics stemming from these identifying factors.
3. Piloting the support course in a randomized controlled experiment.
4. Assessing the effectiveness of the support course.

Significance of Topic

The developmental educational community stands to benefit greatly from a successful development of a concurrent support class. The magnitude of the problem addressed partially by this research can be realized by just a couple of sobering statistics/problems facing the developmental educational community. Below are some quotes and their Internet Sources indicating the current status of developmental education in the United States:

Only 17% of students who enroll in a remedial reading course receive a bachelor's degree within eight years, compared to 58% of students who take no remedial education courses.

http://www.communitycollegecentral.org/Downloads/Developmental_Education_TOOLKIT.pdf.

For the first time in U.S. history, the current generation of college-age Americans will be less educated than their parents' generation, yet our workplaces require higher-level skills than ever before.

http://www.achievingthedream.org/ABOUTATD/OVERVIEW/default.tp.

About 6.8 million students — nearly half of all undergraduates in the U.S. — are being educated at 1,200 community colleges. But too few are reaching their goals. Historically, fewer than half of community college students succeed in earning a degree or transferring to a four-year institution. And more than just their hopes and dreams are at stake: the very foundations of our economy depend on increasing student success.

http://www.achievingthedream.org/Portal/Modules/8f75b350-0a49-4218-bb55-547613 1af73c.asset?.

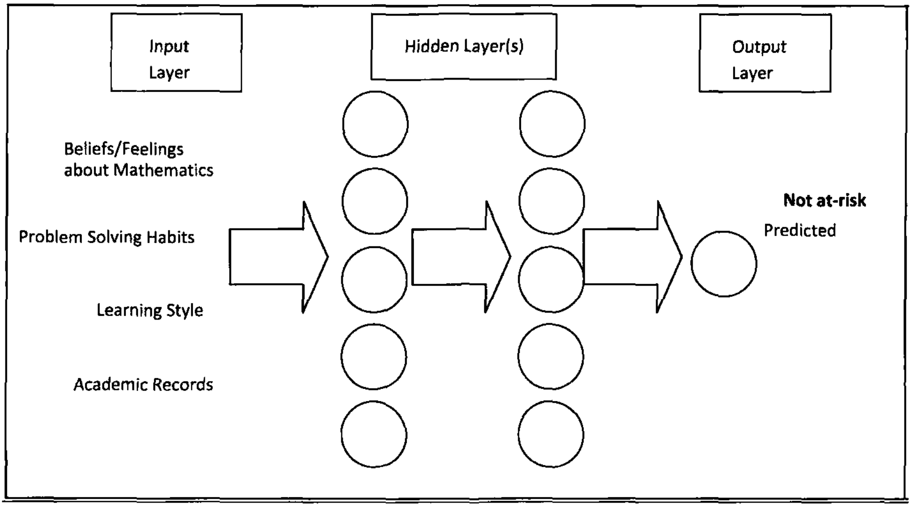
The purpose of this research is to provide a framework for the creation of other concurrent support courses, regardless of discipline.

Methodology

Much of the research behind this article pertains to the creation of an accurate predictive system to identify students who are "at-risk" of not succeeding in TRS 92 – Intermediate Algebra. The author opted to create a neural network to identify "at-risk" students. Neural networks have been shown to be of use in predicting student success in a variety of contexts (Hardgrave & Wilson, 1994; Naik & Ragothaman, 2004; Sexton, Hignite, Margavio, & Satzinger, 2001; Schumacher et al. 2010).

The use of neural networks as a method for predicting student success in a wide variety of contexts predominantly stems from the mathematical proof that multilayer backpropagation networks are universal approximators (Hornik et al. 1989). The process of adjusting weights is referred to as the backpropagation. Given a universal approximator, if a means to map between inputs and outputs exists (i.e. a way to use predictors to accurately predict student success in this context), then the approximator will discover it. A detailed description of the major aspects behind the development and implementation of the predictive system used in this research is available (Cooper, 2007).

The basic schematic, however, of the neural network for this research is depicted below:



For four semesters prior to the pilot support course, students enrolled in Intermediate Algebra were questioned regarding their beliefs/feelings about mathematics, their problem solving habits and learning styles. Items for the Beliefs about Mathematics, Problem Solving Habits, and Feelings about Mathematics were taken directly from the National Council of Supervisors of Mathematics 1994 Supporting Leaders Source Book (NCSM, 1994). This information was then joined with students' academic records and most importantly with their letter grade outcome in Intermediate Algebra.

The data gathered via the input layer formed the input space (i.e. the possible predictors of student success). The author then presented the data from the previous four semesters to the Hidden Layer(s), which comprise the predictive essence of a neural network. Each circle in the diagram above represents a processing element (i.e. artificial neuron). Each processing element creates a weighted sum of inputs and has a threshold function to determine if the neuron "fires" or not. This process represents a rudimentary mathematical model of how neurobiologists believe interconnected neurons within the brain behave. Given the input data paired with known letter grade outcomes for each student record (i.e. whether the student was successful or not), the neural network software adjusted the weights within each processing element according to the desired output.

Before Hornik could derive his universal approximator proof mentioned earlier, a method to train multilayered neural networks needed to exist. In the mid 1980s, David Rumelhart, Geoffrey Hinton, and Ronald Williams (Rumelhart, Hinton, & Williams, 1986) derived the necessary mathematics. Their algorithm has since become known as the backpropagation algorithm and is the most widely used learning rule implemented in neural networks today (Principe, Euliano, & Lefebvre, 2000). In essence, backpropagation measures the error at the output layer and adjusts the weights within the processing elements according to the relative contribution to the error from each of the inputs. The weight adjustment works backwards towards the input layer. As a whole, this process comprises the learning behind the scene of a neural network. Hence, the resultant dataset from the previous four semesters became the foundational learning database for training and testing a neural network to identify "at-risk" students.

Altogether approximately 60 variables were considered as possible predictors. After two stages of a unique three-stage input pruning process, the predictive input space for the neural network was reduced down to eight variables which are described in the table on page 18:

Variable	Description	Measurement
HS_GPA	Student's high school GPA.	GPA
FLC_GPA	Student's current GPA in college.	GPA
Gender	Student's gender.	Male or Female
History_4	Student's ranking of difficulty of "problems involving fractions" relative to other skills.	Ranking in terms of difficulty
History_6	Student's ranking of difficulty of "problems involving percents" relative to other skills.	Ranking in terms of difficulty
Problem_Solving_13	Student's response to "there are some problems I will just not try."	True or False
Problem_Solving_17	Student's response to "most problems are too hard for me to solve."	True or False
Feelings_1	Student's feeling of being "Challenged."	Most of the time, Sometimes, or Almost Never

At this stage, the neural network's accuracy in identifying students as either "at-risk" or "not at-risk" is summarized in the confusion matrix below:

	Actual "at-risk"	***Actual "not at-risk"***
Predicted "at-risk"	$\frac{284}{358} = 79.3\%$	$\frac{104}{322} = 32.3\%$
Predicted "not at-risk"	$\frac{74}{358} = 20.7\%$	$\frac{218}{322} = 67.7\%$
Percent Correct	Predicted "at-risk" accuracy: 79.3%	Predicted not "at-risk" accuracy: 67.7%

During the final stage of the input pruning process, backwards elimination, the variable Gender was eliminated. Backwards elimination entails removing a predictor, rebuilding and testing the neural network. If the accuracy improves, then the predictor is eliminated. The final neural network's accuracy used for production in the controlled pilot experiment is given on page 19:

	Actual "at-risk"	*Actual "not at-2risk"*
Predicted "at-risk"	$\frac{290}{358} = 81.0\%$	$\frac{106}{322} = 32.9\%$
Predicted "not at-risk"	$\frac{68}{358} = 19.0\%$	$\frac{216}{322} = 67.1\%$
Percent Correct	Predicted "at-risk" accuracy: 79.3%	Predicted not "at-risk" accuracy: 67.1%

Of note regarding the categorical predictive accuracies, the initial data was oversampled to balance the two categories and to have a better predictive accuracy for the most important category of interest in the context of this research, "at-risk" students. Oversampling is a common practice in the development of a decision support system and in the field of business intelligence (Shmueli, Patel, & Bruce, 2006; Turban, Aronson, & Liang, 2005). During the process of oversampling, an appropriate number of rows within the dataset are randomly selected and duplicated within the category of interest. The goal is to have an equal number of "at-risk" rows and not "at-risk" rows in order to provide a better accuracy for the population of interest. In this case, the category of interest, "at-risk" students was oversampled. A cautionary note should be made. If a researcher oversamples too much, then the predictive system can lose much of its generalizability. In other words, the neural network will not be able to predict outcomes of new student records in an actual prediction/placement setting. In the end, the predictive system correctly identified 81% of the "at-risk" students and had an overall accuracy of 74.4%. Thus, the predictive system correctly identified approximately three fourths of the students taking Intermediate Algebra.

The salient predictors listed in the table above were shown to two content experts for input regarding the creation of an effective concurrent support course. The first content expert was Dr. Brian Burke, a practicing clinical psychologist and associate professor at Fort Lewis College (B. Burke, personal communication, October 14, 2006) with a specialization in motivational interviewing. The second content expert was the late Dr. Lew Romagnano, an associate professor at Metropolitan State College of Denver and past President of the Colorado Council of Teachers of Mathematics (CCTM) with a specialization in mathematics education and assessment (L. Romagnano, personal communication, October 28, 2006).

Several of the pedagogical suggestions offered by Dr. Burke are given on page 22:

1. academic skills building activities.
2. purposeful use of the Algebra Alcove, a one-on-one, drop-in tutoring center at Fort Lewis College available to students taking mathematics courses free of charge.
3. study logs.
4. motivational interviewing activities.
5. problem solving techniques.
6. manipulative based mathematics education.
7. math anxiety mitigation techniques.

Additionally, several of the pedagogical suggestions given by Dr. Romagnano are listed below:

1. specific practice with problems.
2. reading for comprehension within the context of mathematics.
3. organizational skills as a subset of basic academic skills.
4. mixed grouping of students for gender issues and level issues.
5. problem solving strategies.
6. math anxiety coping skills.
7. meta cognition during the problem solving process.

The author, in consultation with the instructor of the pilot course and the content experts, outlined a 15-week support course that addressed many of the pedagogical interventions listed above (especially interventions jointly listed by the two external experts (i.e. problem solving techniques and math anxiety mitigation techniques)). The course ultimately became a one credit, one hour per week pass/fail course. In addition to the one-hour per week class time, students were required to spend at least one hour in the Algebra Alcove per week. Algebra Alcove logs offered the means to track students' satisfactory completion of this requirement. The final details/topics for the course are detailed in the table below.

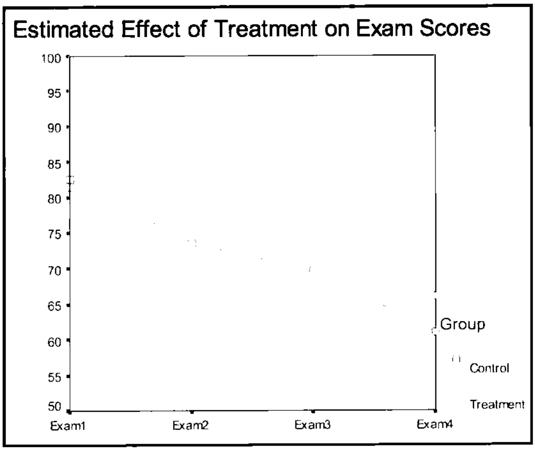
The experiment for the concurrent course pilot entailed identifying "at-risk" students via the neural network and subsequently offering "at-risk" students the option of taking the concurrent support class. All of the students willing to take the concurrent support class were randomized into either a treatment (N = 22) or a control group (N = 20). The treatment group consisted of students who were identified as "at-risk," willing to take the support course, and randomly selected for enrollment into the support course. The class did not begin until week 3 due to the neural network placement and enrollment processes. In all, the author views the course as being comprised of six units, three of which are directly tied to exam preparation and practice.

Unit	Week	Activities/Topics	Description and Rationale behind topic(s) choice
UNIT 1	Week 3	Motivational interviewing discussion and worksheet developed in consult with Dr. Burke.	**Psychological underpinnings** to success in developmental mathematics were presented and discussed. Topics included motivation interviewing, which was conducted by Dr. Brian Burke in the class. Motivational Interviewing has been shown to have a significant impact in behavioral change in variety of contexts (DiLillo, V. & West, D.S., 2011; Markland D. et al. 2005; Stein, L. A. & Lebeau-Craven, R., 2002). The activities conducted by Dr. Burke helped students measure their desire/motivation to obtain a bachelors degree and thereby helped students realize the importance of succeeding in Intermediate Algebra. Math anxiety and anxiety mitigation technique were also presented by Dr. Burke. As evidenced by the outcomes on the second exam (see graph below), Dr. Burke made a significant impact on student performance. It is the author's opinion that a competent presentation of these topics, motivation and anxiety, can be offered by local professional counselors. In fact, subsequent iterations of the course were not able to have the in-class services of Dr. Burke, but a licensed psychologist was willing to donate his time. The positive outcomes were similar.
	Week 4	Discussion of math anxiety and methods to mitigate the symptoms and effects.	
UNIT 2	Week 5	Calculator usage as means to visualize mathematics and to problem solve. Fraction practice via manipulatives and discussion of various fraction models.	***Fundamental skills*** were covered during these two weeks. The skills covered included: calculator usage for mathematics visualization, problem solving techniques, and basic mathematic skill review (e.g. review of fractions and percentages since these specific topics were directly tied to neural network predictors).
	Week 6	Test preparation skills and techniques presentation and discussion, which led into a discussion of overall academic study skills.	
UNIT 3	Week 7	Exam #2 review and preparation via problem solving practice and techniques.	**Review and preparation for Exam 2**. Test taking techniques were discussed in reference to the specific topics to be covered and in reference to the math and test taking anxiety discussed earlier in the term.
	Week 8	Exam #2 review and preparation continued.	
UNIT 4	Week 9	Exponent practice via manipulative. Negative exponents emphasized and discussed via further manipulative practice.	While understanding and ***familiarity with exponent rules*** was not found to be an important predictor, the instructor of the support course has found the rules to

			be stumbling blocks for students on Exam 2 and Exam 3. Thus, the instructor offered an alternative problem solving in mathematics are available (Barb, C., 1997; Mikusa, M.G.,1998). These problems do not have quick/simple answer and require a higher degree of cognitive demand. The goal of these problems was to instill a certain level of frustration and discuss why frustration is not necessarily a bad thing and can in fact be a good thing as long as you can get through it.
UNIT 7	Week 14	Final review.	**Open-ended summative review** of the semester and discussion of how to prepare for the final exam given the material presented during the support class.
	Finals Week		

Results

Effect Size Analysis Data across the semester was collected to measure the impact of the treatment, the concurrent support course. Mainly, students' exam scores for both the treatment and control groups were collected and compared. Exams were given approximately every four weeks throughout the 15-week semester. The concurrent support class had little or no impact on Exam 1 performance for the treatment group since, as mentioned earlier, the third week was the first week for the support course. After Exam 1, however, students in the treatment group consistently had statistically significant higher exam scores across the entire semester. No statistically significant difference was realized for the first exam, which offers good evidence of an effective randomization. The differences in exam scores across the entire semester between the two groups are depicted in the graph below:



The differences between the exam scores for the treatment and control were quantitatively compared via Cohen's d. Cohen's d provides a measure of effect size commonly used in meta-analysis. Statistically, Cohen's d creates a standardized difference between two means, which provides a measure of the magnitude of the treatment effect (Cohen, 1988). One can holistically treat Cohen's D as a counterpart to statistical significance. While statistical significance indicates the existence of a difference, effect size as measured by Cohen's D is a measure of the size of the realized difference. A complementary statistic to Cohen's d is the distribution overlap, U3. "This statistic describes the percentage of scores in the lower-meaned group that are exceeded by the average score in the higher-meaned group" (Valentine, J. C. & Cooper, H., 2003). The table below summarizes these metrics for the exam averages for both groups over the entire semester.

Effect Size Measures

Assessment	**Cohen's d**	**U3**	**Improvement index**
EXAM1	-0.11	46%	-4%
EXAM2	0.64	74%	24%
EXAM3	0.48	68%	18%
Final Exam	0.20	58%	8%
Course	0.30	62%	12%

While uncomfortable with a strict categorization, Cohen labeled values from his metric as small, medium, or large effects with approximate corresponding values of Cohen's d=0.2, d=0.5, and d=0.8 (1988, p. 25). With Cohen's interpretation of effect size measure in mind, there was little to no effect of the treatment (d=-0.11) at the beginning of the semester, which supports the intention of creating a true randomization of participants. As evidenced by Cohen's d in the table above, the effect of the treatment was the strongest during the middle portion of the semester. A smaller effect size was noted for the final exam and the course average as a whole.

As a companion statistic to Cohen's d, the distribution overlap, U3, is also given in the table above. U3 offers a more intuitive and accessible interpretation of effect size. As an example, the distribution overlap, U3, for Exam3 is 68% which corresponds to an 18% Improvement index. In other words, for an average person in TRS 92 - Intermediate Algebra (i.e. at the 50th percentile), the person can expect to move up to the 68th percentile by taking the concurrent support class. At the end of the semester, an average student could expect a 12 percentage point increase in his or her percentile ranking by taking the concurrent support class.

As a means to measure the overall effect size of the concurrent support class, an exam average across all exams was calculated for the students in the treatment and control groups. Students in the treatment had an overall exam average of 77.6%, and students in the control had an overall exam average of 71.7%. This equated to a Cohen's d of 0.43 and an improvement index of 17%. Hence, an average student could expect a 17 percentage point increase in his or her percentile ranking in reference to their exam performance across the semester.

In terms of success/failure rates between the treatment and control, these can be assessed via the 2x2 contingency table below:

	Treatment	**Control**	**Row Total**	**Treatment**	**Control**
Pass	16	12	N=28	[illegible] = 72.7%	[illegible] = 60.0%
Fail	6	8	N=14	[illegible] = 27.3%	[illegible] = 40.0%
Column Total	N=22	N=20	Total=42		

The treatment group had a 73% success rate with a corresponding 27% failure. The control group had a 60% success rate with a corresponding 40% failure rate. The differences in experimental success rates were not statistically significant as measured by the Pearson Uncorrected chi square test of independence $\chi 2\ (1, n = 42) = 0.764$, $p = 0.382$. The Pearson Uncorrected chi square test can be treated as a test of equality of proportions where the null hypothesis is the proportion of pass versus fail is the same for the Treatment and Control. The alternative hypothesis is the proportion is not the same for the Treatment and Control. In this case, with p-value of 0.382, one can not reject the null hypothesis. In other words, there was no statistically significant difference realized in the Treatment in the proportion of pass versus fail. One explanation for absence of a statistically significant difference is the lack of power. Without enough statistical power, an increased probability of a false null hypothesis exists. One way to increase statistical power is to have a larger value for n, sample size. Multiple offerings of the concurrent support class over multiple semesters provided a much larger sample size. An analysis of these results is provided on page 27:

Longitudinal Results

With the pilot course, offered in the Winter Semester 2007, being a success as measured by effect size, it was decided by the school to offer the concurrent support course subsequent semesters. By the end of the Fall Semester 2009, 39 students had successfully completed the concurrent support class. Of the 39 students successfully completing the support class, 32 students passed TRS 92 – Intermediate Algebra for a student success rate of 82%, or conversely a student failure rate of 18%. This is notably better than the almost 40% failure rates seen nationally and at Fort Lewis College historically. Even more noteworthy is that the 82% success rate stems from a student body that was identified as being "at-risk" by an accurate predictive system. Most of these students were not likely to succeed in TRS – Intermediate Algebra. This provides the strongest evidence in support of the efficacy of the concurrent support course.

During the same timeframe, from Winter 2007 to Fall 2009, 689 Intermediate Algebra students did not take the concurrent support course. Of the 689 students who did not take the support class, 433 students passed TRS 93 – Intermediate Algebrea for a student success rate of 63%, or conversely a student failure rate of 37%. In other words, the student failure rate more than doubled compared to the 18% for students taking the support class.

Even though a statistically significant difference in success rates was not realized between the treatment and control groups for the pilot, one can take a broader perspective and determine if significant difference is found in the long run offering of the support class. Indeed, per the Pearson Uncorrected chi square test for equality of proportions, the differences in success rates between students who completed the concurrent support class and students who did not take the course was statistically significant $\chi 2$ (1, n = 728) = 5.901, p = 0.015.

Further Research

This research only considers one primary form of intervention, a concurrent support course. Other interventions may also be as or even more effective for the "at-risk" student body identified within this research. Effective interventions might include personalized academic advising & monitoring, peer mentoring, early alerts, referrals to online support resources and/or existing academic support programs. Central to this research is the use of preexisting data to form the training and testing dataset for the neural network. Student bodies are in continuous state of flux. Thus, research to determine when data should be considered obsolete should be conducted. It is the author's opinion that this will have to be done by individual institutions since every institution has its own idiosyncratic student body. Finally, while this research is intended to offer a framework for the creation of concurrent support courses independent of discipline. Research should be conducted to see if the approach taken within this research is applicable to other discipline other than developmental mathematics. Testing the generalizability of this research in regards to other disciplines, however, would entail the use of a valid and reliable instrument such as the NCSM questionnaire utilized for this research. The instrument could be either be preexisting, a modified version of a preexisting instrument, or a completely new instrument. Regardless, a substantial amount of work would need to be conducted in order to ensure a well-tested instrument with meaningful potential predictors is being used.

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