Rethinking the Effects of Classroom Environments on Student Learning in a Large School System

Michael Dryden & William J. Webster
Dallas Public Schools
3700 Ross Avenue
Dallas TX 75204, USA

Barry J. Fraser
Curtin University of Technology
GPO Box U1987
Perth 6845, Australia

Objectives or Purpose

Many environmental factors assumed to be part of the classroom, like friction and perceptions of difficulty, may have greater influence on the student outside the classroom. Similarly, some classroom environmental factors previously shown to have a weak relationship to learning may actually have a large effect. At issue is whether the researcher is measuring student learning due to the effects of the classroom, or achievement due to the effect of the classroom plus factors outside the classroom. Until the recent introduction of multilevel modeling and hierarchical linear modeling (Raudenbush & Bryk, 1988), measures of classroom-based learning have been subject to accuracy and precision. The purpose of this study was to investigate whether the relationships between the learning environment and student learning shift when exogenous variables unrelated to the classroom are removed using multi-level modeling.

Theoretical Framework

In a large, heterogeneous school system, the relationship between achievement and learning environment is significant but not strong (Dryden & Fraser, 1996). The heterogeneity of the student population in large systems may explain this low relationship. Achievement, as measured by current standardized tests, is laced with ability and home learning factors. In this study, it was hypothesized that there is a difference between 'student achievement' and 'student learning due to the classroom'. If an accurate measure of student learning could be devised, then the predictive relationship between student perceptions of the learning environment and classroom learning could be examined.

To date, no literature has been found examining the relationship between classroom-based learning that uses multi-level modeling and the learning environment in a very large system. The literature shows that the relationships between achievement and student perceptions of the learning environment are generally positive (Fraser, 1994, 1998; Fraser & Walberg, 1991). However, most studies involve achievement, not learning, as the outcome measure. In a meta-analysis, Haertel, Walberg, and Haertel (1981) showed that regression-adjusted gains were consistently and significantly related to cognitive and affective outcomes. In general, these relationships were strongest with older students and when the classroom or school was used as the unit of analysis.

Noonan and Wold (1982) attempted to measure learning efficiency using the IEA chemistry subtest on the assumption that chemistry is learned primarily in the classroom and is more dependent on school instruction than in many other subjects. According to Noonan, the level of learning or probability of a correct response is given by:

$$L = p = 1 - (1 + p^*)^{t/t*} = 1 - (q^*)^{t/t*,}$$

where p* is an arbitrarily defined level of learning, q* = 1 - p*, and t* is the amount of time on a given learning activity required to reach the level p*. Noonan then defined the rate of learning as

$$R= dp/dt = -(1/t^*)(q^*)^{t/t^*} \ln(q^*)$$

and the efficiency of learning as the ratio of learning to the probability of an incorrect response, or:

$$E = (dp/dt)/q = (-\ln(q^*))/t^*$$

This measure indicates that learning efficiency is fairly constant over the range of the learning curve and time is not important for the efficiency of learning. In other words, the efficiency of learning quickly becomes constant over time. It is this spirit of learning efficiency versus learning rate that is the foundation of the multilevel analysis that follows. Noonan was constrained to use a 'schoolish' subject like chemistry. In this study, using a hierarchical linear model of one of the authors (Webster et. al., 1997), it is believed that a technique for measuring classroom learning efficiency as opposed to student achievement has been devised and the constraints of using a school-based subject have been lifted. In a large heterogeneous school system, these distinctions are of critical importance. Experience shows that learning and the rate of learning is also highly dependent on factors outside of the classroom. At issue in an urban school is the efficiency of learning which is attributable to classroom or school effects only, independent of varying abilities and opportunities to learn outside the classroom.

A classical dilemma in achievement-environment studies is causal order. Does a positive environment produce higher achievement or do high performing students create a positive environment? In this study, causal order is predetermined because learning efficiency is a function of what happens in the classroom, by definition. As will be shown in the next section, learning efficiency is based on a methodology that attempts to partial out as many prior influences as possible. It is an outcome variable that is determined by influences in the classroom.

Measuring Learning Efficiency

The Dallas Public Schools defines student-level learning efficiency as being associated with exceptional measured performance above or below that which would be expected across the entire District. When a student departs markedly from his or her own pre-established trend or, more exactly, from the general trend of similar students throughout the District, this departure is attributed to school or classroom effects. The problem of measuring learning efficiency, then, becomes one of establishing the student's level of accomplishment on the various important outcome variables, setting levels of performance based on these expectations, and determining the extent to which the student, on average, exceeds or falls short of expectation. The procedures involve the use of hierarchical linear modeling with student-level variables and multiple regression analysis with aggregate school-level variables to compute prediction equations by grade level for each outcome variable, and then using those equations within schools to obtain gains over expectations.

The first step in developing the learning efficiency methodology involves what educational practitioners have called 'leveling the playing field'. The first step in developing the equations was to eliminate the variance in outcomes associated with student contextual variables over which the schools had no control. To accomplish this, each outcome and predictor variable was regressed on a set of important student background variables and their interactions to produce a set of residuals for each of the predictor and outcome variables (Webster, Mendro, & Almaguer, 1992).

The basic OLS regression model is generated from the standard OLS equation. This is represented by equation 1 for student-level variables:

$$Y_i = \beta_0 + \beta_1 X_i + r_i \tag{1}$$

where

$$r_i \sim N(0, \sigma^2)$$

Using this model, the *Y*s represents any of the predictor or outcome variables in the system. The *Xs* represent predictor variables used in the first-stage equations. (These values are student demographic variables without reference to school at the moment.) After a solution is found for each *X*, the model is solved for each student and the value of the residual r_i is determined. This value of *r* represents the portion of the student's score that can be attributed to background variables plus any individual error for the student on the particular outcome measure *Y*. This equation is solved for each of the possible *Y* variables and the student residuals determined for each student. Student level variables included in the first stage are:

Y_{ij}	=	Outcome variable of interest for each student *i* in school *j*
X_{1ij}	=	Black English Proficient Status (1 if black, 0 otherwise)
X_{2ij}	=	Hispanic English Proficient Status (1 if Hispanic, 0 otherwise)
X_{3ij}	=	Limited English Proficient Status (1 if LEP, 0 otherwise)
X_{4ij}	=	Gender (1 if male, 0 if female)
X_{5ij}	=	Free or Reduced Lunch Status (1 if subsidized, 0 otherwise)
X_{6ij}	=	Block Average Family Income
X_{7ij}	=	Block Average Family Education
X_{8ij}	=	Block Average Family Poverty Level
X_{kij}	=	Indicates the variable *k* of i^{th} student in school *j* for $i = 1,2, \ldots, I_j$ and $j = 1, 2, \ldots, J$.

The stage one equations appear as follows:

$$\begin{aligned} Y_{ij} = \; & \Lambda_0 + \Lambda_1X_{1ij} + \Lambda_2X_{2ij} + \Lambda_3X_{3ij} + \Lambda_4X_{4ij} + \Lambda_5X_{5ij} + \Lambda_6X_{6ij} + \Lambda_7X_{7ij} + \Lambda_8X_{8ij} + \\ & \Lambda_9(X_{1ij}X_{4ij}) + \Lambda_{10}(X_{2ij}X_{4ij}) + \Lambda_{11}(X_{3ij}X_{4ij}) + \Lambda_{12}(X_{1ij}X_{5ij}) + \Lambda_{13}(X_{2ij}X_{5ij}) + \\ & \Lambda_{14}(X_{3ij}X_{5ij}) + \Lambda_{15}(X_{4ij}X_{5ij}) + \Lambda_{16}(X_{1ij}X_{4ij}X_{5ij}) + \Lambda_{17}(X_{2ij}X_{4ij}X_{5ij}) + \\ & \Lambda_{18}(X_{3ij}X_{4ij}X_{5ij}) + r_{ij} \end{aligned}$$

The first stage OLS regression equations include first- and second-level interactions. These equations account for 9–20% of the variance in student achievement.

Hierarchical linear modeling is then used on the residuals of both the outcome and predictor variables. Student level equations are developed utilizing individual student data rather than school means. Satisfactory prediction was achieved in all cases without having to go back more than one year ($R^2 \geq .70$). This maintained the degrees of freedom associated with the equations.

The standard equations for the random effects HLM model are given in equations 2-4 for a single level 1 predictor and a single level 2 conditioning variable. Note that level 1 contains a model of school-level data. The two types are modeled simultaneously in an HLM model. As for data in the case of the OLS regression model, these equations can be expanded by the inclusion of more level 1 student predictor variables (X) and more level 2 school conditioning variables (W). School effects are estimated directly from shrinkage-adjusted empirical Bayes residuals resulting from the application of the HLM model (Bryk & Raudenbush, 1992). A series of research papers developed by Dallas staff contain more explicit formulations of the model under many different conditions. The interested reader is referred to Webster et. al. (1995, 1996, 1997, 1998), Mendro et. al. (1995), Orsak, (1997), or Weerasinghe, et. al., (1997), for more detailed models and discussions of these applications.

Level 1 $$Y_{ij} = \beta_{0j} + \beta_{1j} X_{ij} + r_{ij} \quad (2)$$

Level 2 $$\beta_{0j} = \gamma_{00} + \gamma_{01} W_j + u_{0j} \quad (3)$$

$$b_{1j} = g_{10} + g_{11} W_j + u_{1j} \quad (4)$$

where

$r_{ij} \sim N(0, \sigma^2)$

$u_{0j} \sim N(0, \tau_{00})$

$u_{1j} \sim N(0, \tau_{11})$

$Cov(u_{0j}, u_{1j}) = \tau_{01} = \tau_{10}$

The HLM models utilized in Dallas are two-stage, two-level random models that include a number of school-level contextual variables:

W_{1j}	=	School Mobility
W_{2j}	=	School Overcrowdedness
W_{3j}	=	School Average Family Education
W_{4j}	=	School Average Family Education
W_{5j}	=	School Average Family Poverty Index
W_{6j}	=	School Percentage on Free or Reduced Lunch
W_{7j}	=	School Percentage Minority
W_{8j}	=	School Percentage Black
W_{9j}	=	School Percentage Hispanic
W_{10j}	=	School Percentage Limited English Proficient
W_{11j}	=	School Percentage Teacher Instructional Days Lost to Medical Disability and Unfilled Vacancies.

The stage two equations appear as follows:

Level 1:

$$\text{Criterion Variable\_R\_POST}_{ij} = \beta_{0j} + \beta_{1j} R_1\_PRE_{ij} + ... + \beta_{nj} R_n\_PRE_{ij} + d_{ij}$$

where

$\text{Criterion Variable\_R\_POST}_{ij}$ = posttest residual from stage one

R_n_PRE = n^{th} pretest residual from stage one

$$d_{ij} \overset{iid}{\sim} N(0, s^2).$$

Level 2:

$$\beta_{kj} = \gamma_{k0} + \gamma_{k1}W_{1j} + \gamma_{k2}W_{2j} + \ldots + \gamma_{k11}W_{11j} + u_{kj}$$

for $k = 0, 1, 2, ..., n$.

$$E[u_{kj}] = 0, \text{ Var/Cov}[u_{kj}] = T, \text{ and } u_{kj} \perp d_{ij}$$

$$\text{The Learner Efficiency Index} = LEI_j^* = u_{0j}^*$$

In summary, the models have the following steps:

1. School variables are predicted in a regular OLS regression using two years of prior data on outcome variable. Effectiveness scores are computed from the residuals of the regression. School level variables have not been discussed in this paper but involve the use of basic OLS regression models to obtain school-level residuals. (For details about the school level models, see Webster et.al., 1998).

2. Student variables are predicted from two-stage, two-level modified OLS regression and HLM models.

3. The first stage of the student variable process regresses outcome variables and prior predictor variables against student-level concomitant variables, adjusts the residuals for homogeneity, and provides residuals for the HLM stage.

4. The second stage of the student variable process uses one year of prior level residuals from the first stage to predict the outcome residuals from the first level in a two-level HLM random effects model with an array of school-level conditioning variables at the second level.

5. The results of each HLM analysis by student outcome variable and the school-level outcome variable OLS regressions are standardized.

6. Finally, the residual based on the modeled intercept, u_{0j}^*, is used to give an estimate of classroom learning efficiency.

The Learner Efficiency Index (LEI) includes a number of criterion variables. Student-level variables include *Iowa Tests of Basic Skills*, grades k through 8, reading and mathematics; *Tests* *of Achievement and Proficiency,* grade 10, reading and mathematics; student attendance; *Texas Assessment of Academic Skills,* grades 3 through 8 and 10, reading, mathematics, writing, social studies, and science; *Texas Assessment of Academic Skills-Spanish,* grades 3 through 6, reading, writing, and mathematics; *Spanish Assessment of Basic Education*, grades 1 through 6, reading and mathematics; *Assessments of Course Performance,* grades 9 through 12, reading/language arts, mathematics, social studies, science, world languages, and ESOL; *Woodcock-Munoz Language Survey,* grades 1 through 6; *Scholastic Aptitude Test,* verbal and quantitative; *American College Test;* and *Preliminary Scholastic Aptitude Test,* verbal and quantitative. School-level variables include promotion rate, graduation rate, percentage of students tested on the *Preliminary Scholastic Aptitude Test,* the *Scholastic Aptitude Test,* and the *American College Test*, dropout rate, percentage of students enrolled in pre-honors and honors courses, percentage of students enrolled in advanced placement courses, and percentage of students passing advanced placement examinations.

Measuring Classroom Learning Environment

The learning environment was measured using a locally modified version of the My Class Inventory (MCI) in both English and Spanish (Fraser & O'Brien, 1985). The scales in the *MCI*, as in the original version, are *Satisfaction* with learning, *Cohesion* among students, classroom *Friction*, student *Competition*, and the *Difficulty* of classwork. In a prior study, these measures were found to be highly reliable and valid for the population in this study (Dryden & Fraser, 1996). Classroom learning environments were taken as the aggregate of student scale scores. This practice is not as sensitive as the one proposed by Raudenbush and others (1989) where they used multilevel modelling to partition the variance in climate scales between and within schools.

Context of the Learning Efficiency and Learning Environment Relationship

The relationship between classroom learning efficiency and the learning environment has little meaning out of context. This context was established over the past two years by more than 15 evaluators performing over 250 classroom observations. What the evaluators recorded should match the results of this study. This use of both qualitative and quantitative research is strongly recommended by Fraser and Tobin (1991) and Tobin and Fraser (1998) and gives further validity to the research of this project.

Data Sources

A total of 5802 grade 4-5 students in 296 classes responded to the *MCI* and had matching *ITBS* mathematics scores. As mentioned previously, during the past two years, more than 15 evaluators observed over 250 classrooms.

Results

Using the 50 grade 4 and grade 5 classes observed during the 1996-97 school year, highlights of a much larger evaluation study are presented below for the purpose of documenting the nature of instruction in grade 4-6 mathematics classes.

Table 1

Mean Percentage of Time Spent on Each Student Activity in Grades 4-6

Type of Student Activity	Mean Percent
Short answer exercise	25.0
Extended problem solving	2.8
Manipulatives/hands-on	6.0
Listening (3 minutes+)	5.9
Listening and responding	36.4
Interactive discussion	2.8
Computer	9.3

Note: The total is not 100% because only selected activities are presented.

Table 2

Mean Percentage of Time Spent on Each Teacher Activity in Grades 4-6

Type of Teacher Activity	Mean Percent
Teacher presentation of content	11.2
Guided discussion	29.7
Student presentation	1.1
Individual seatwork	18.8
Pairs/groups seatwork	8.8
Small group instruction	1.0
One-on-one instruction	.7
Computer-assisted instruction	9.0
Test practice	5.5
Checking/grading	4.7
Tests	1.1
Directions for assignments	2.1
Discipline/behavioral	.2
Procedural/administrative	3.7
Waiting time	.9
Non-academic activity	1.7

Note: The total is not 100% because only selected activities are presented.

Table 3
Materials Used by Students in the Classroom

Student Materials/Equipment	N	%
Textbooks	7	14.0
Computer	9	18.0
Chalkboard	12	24.0
Manipulatives	12	24.0
Worksheet/workbook	19	38.0
Paper/pencil	31	62.0

Note: The interpretation of this table is that 14.0% of the Grade 4-6 classes observed had students using textbooks.

Clearly, instruction is very passive and teacher controlled. Workbooks and paper and pencil are the most used materials. Most of the teacher time is spent presenting content material or guiding students through an understanding of old materials by using a discussion format. The most common student activities were listening and responding and doing short-answer exercises. In short, teacher control is very important. Because of this, very little classroom friction was ever observed anywhere. Instead, classes were inundated with worksheets and sample problems to practice for the state test. They worked in isolation of each other and seemed very bored.

<u>Exploring the Relationship between Learning Efficiency and Classroom Learning Environment</u>

Using the five MCI scales as predictors and the learning effectiveness index as the criterion measure, a simple stepwise regression was performed at grades 4 and 5. Tables 4 and 5 show the results for grade 4 learning efficiency and achievement, respectively.

Table 4
MCI Scales as Predictors of Mathematics Learning Efficiency for Grade 4

	Mean	Std Dev.
Learning Efficiency	.000	1.000
Satisfaction	86.7	7.8
Friction	49.3	12.2
Competition	61.2	9.4
Difficulty	28.1	10.3
Cohesion	76.6	11.2
Class Size	17.9	3.6

Note: Scale is 0 = no 100 = yes.
N of Classes = 150

Multiple R .30

Variable	Beta	T	Sig T
SATISFACTION	.306798	3.646	.0004
COHESION	-.188642	-2.242	.0265
(Constant)		-2.331	.0211

Table 5
MCI Scales as Predictors of Mathematics Achievement for Grade 4

	Mean	Std Dev
Achievement	53.3	10.236
Satisfaction	86.7	7.7
Friction	49.4	12.2
Competition	61.5	9.5
Difficulty	28.7	10.7
Cohesion	76.7	11.2
Class size	17.9	3.6

Note: Scale is 0 = no 100 = yes.
N of Cases = 150

Multiple R .23

Variable	Beta	T	Sig T
FRICTION	-.23	-2.9	.00
(Constant)		18.5	.00

Table 6
MCI Scales as Predictors of Mathematics Learning Efficiency for Grade 5

	Mean	Std Dev
Learning Efficiency	.0	1.0
Satisfaction	84.8	7.7
Friction	46.6	10.7
Competition	59.0	9.3
Difficulty	26.0	8.7
Cohesion	78.9	9.2
Class Size	21.6	4.8

Note: Scale is 0 = no 100 = yes.
N of Cases = 146

Multiple R .37

Variable	Beta	T	Sig T
SATISF1	.28	3.5	.00
FRICTI1	-.198	-2.4	.02
(Constant)		-2.2	.03

Table 7
MCI Scales as Predictors of Mathematics Achievement for Grade 5

	Mean	Std Dev	Label
Achievement	50.0	9.9	
Satisfaction	84.8	7.8	
Friction	46.8	10.8	
Competition	59.2	9.3	
Difficulty	25.9	8.7	
Cohesion	78.9	9.3	
Class Size	21.5	4.7	

Note: Scale is 0 = no 100 = yes.
Number of classes = 141

Multiple R	.34		
Variable	Beta	T	Sig T
FRICTIION	-.27	-3.3	.00
DIFFICULTY	-.20	-2.4	.02
(Constant)		15.910	.0000

The multiple regression results show that, at both grade levels, learning efficiency is predicted by satisfaction with learning, but achievement is not predicted by satisfaction with learning. Figure 1 and figure 2 illustrate how satisfaction has a direct relationship with achievement for high performing classes, only, and a direct relations with learning across the sample. Of particular interest is the fact that friction is related to learning efficiency at grade 5 and cohesion has an unexpected negative relationship to learning efficiency at grade 4. An inspection of various scatter plots illustrates that learning efficiency is not linear and that, in most cases, for learning to be effective a certain cut-off must be reached. In other words, classroom learning is effective when the classroom satisfaction with learning rating is above 80, friction is less than 40, and cohesion is greater than 80. Otherwise, there is no clear pattern between learning effectiveness and learning environment scales. It is interesting to note that the three environment scales related to learning effectiveness (satisfaction, friction and cohesion) are all classified as ‘relationship dimensions’ in Moos’s (1973) three-dimensional system for describing all human environments.

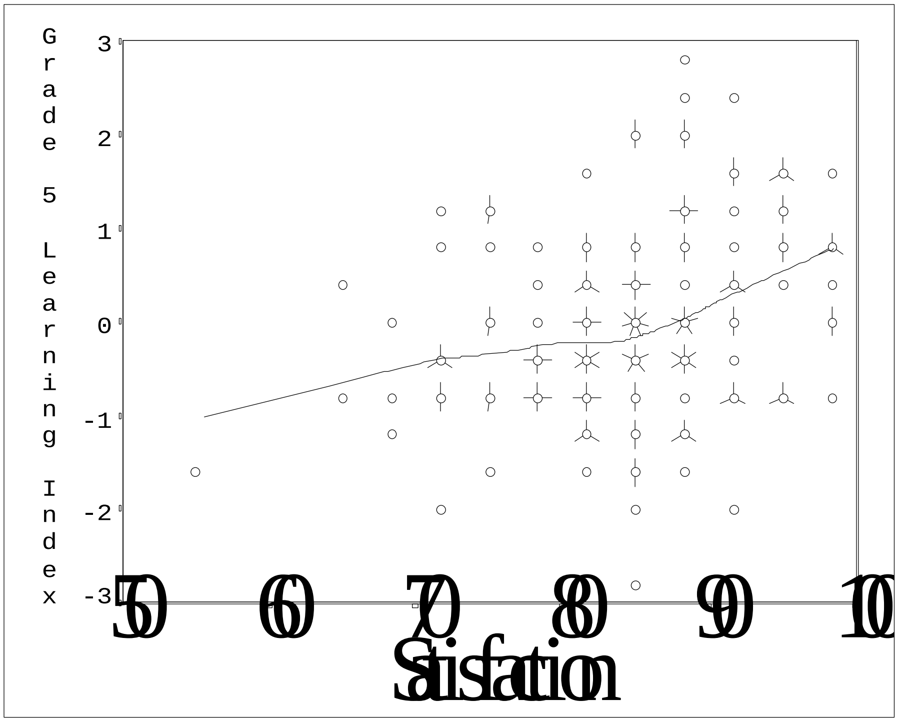

Figure 1. The relationship between satisfaction with learning and fifth grade learning, grade 5
Note: The scale of no = 0 and yes = 100 was aggregated to the classroom level.

Trend: Satisfaction with learning has a direct relationship with learning for all students.

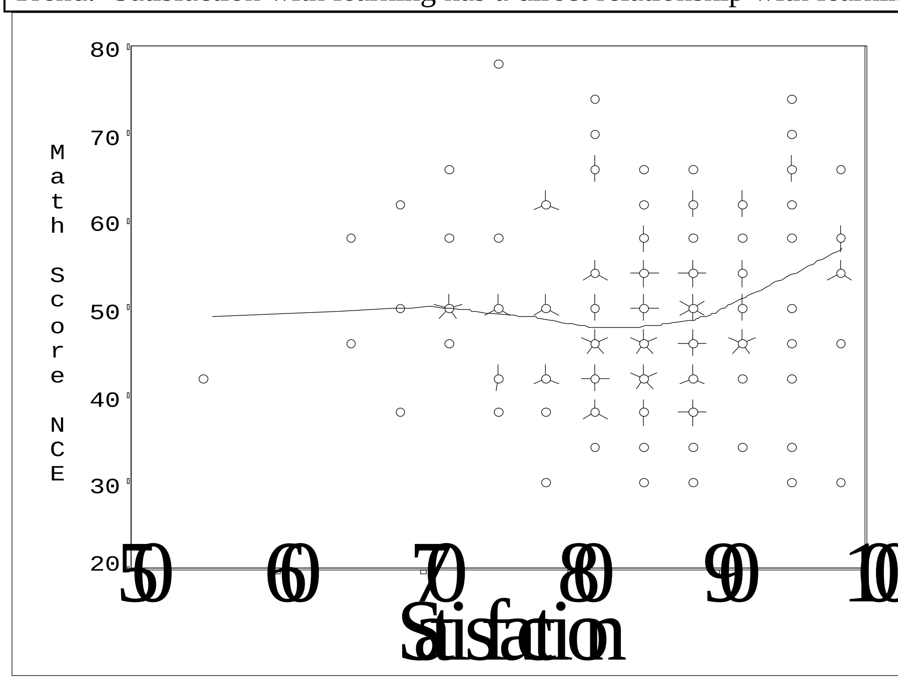

Figure 2. The relationship between classroom perceptions of difficulty and Math ITBS NCE score (achievement), grade 5

Trend: Achievement is not related to satisfaction with learning except for students with the highest satisfaction ratings

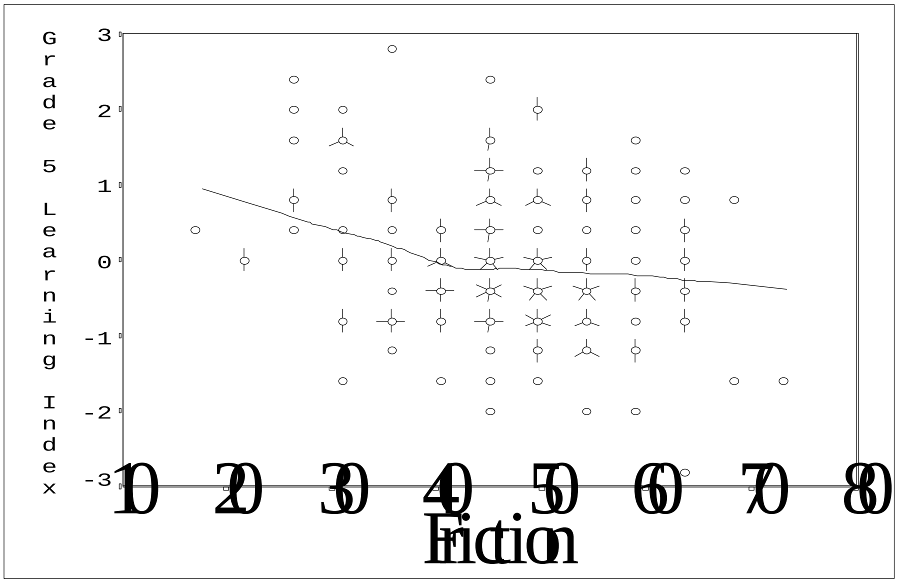

Figure 3. Relationship between friction and learning efficiency, grade 5.

Trend: In classes with higher friction, learning is not related to friction. Learning is better in classes with lower friction.

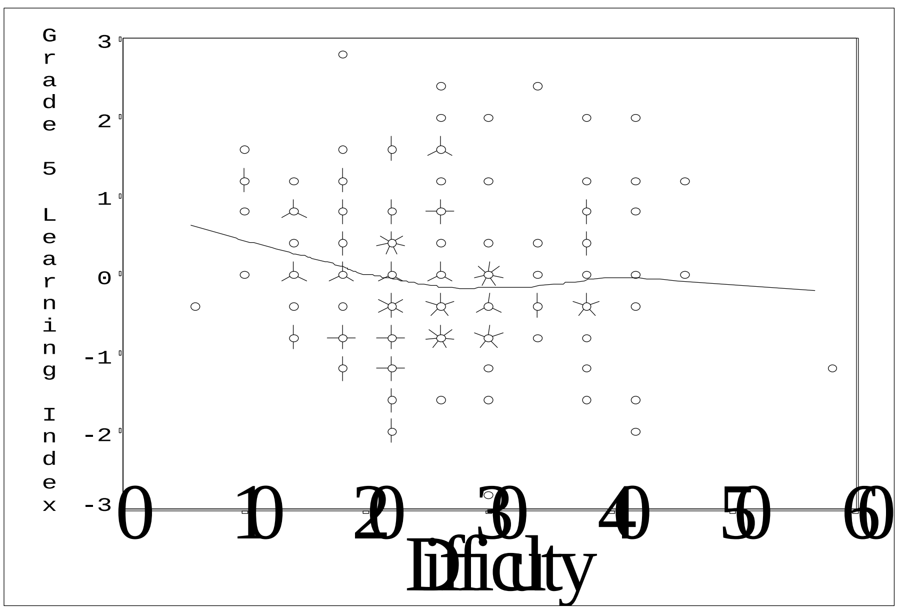

Figure 4. Relationship between difficulty and learning efficiency, grade 5.

Trend: Student-perceived classroom difficulty has little to do with classroom learning, except that students with a very low difficulty rating (i.e., they think it is easy) have higher learning indices.

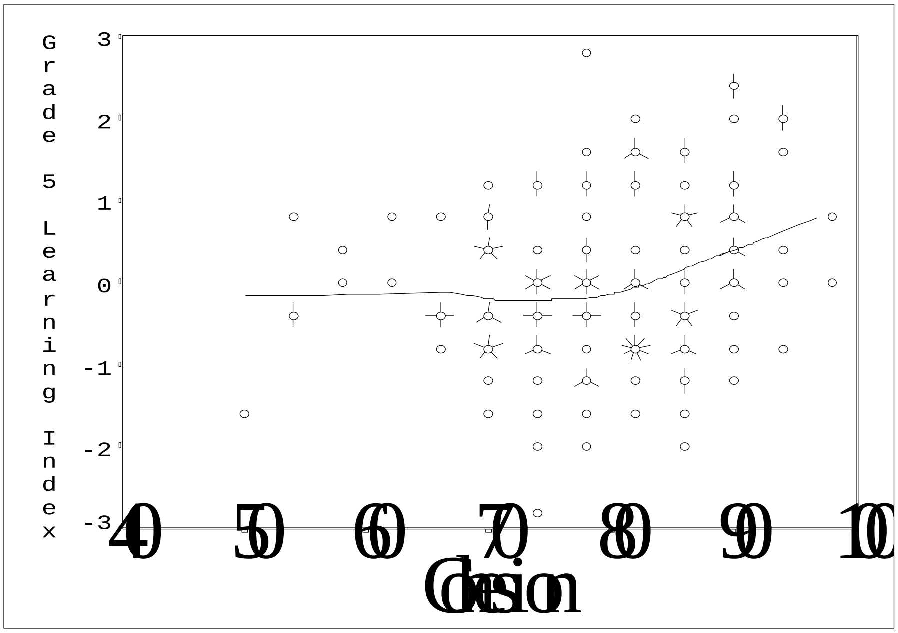

Figure 5. Relationship between cohesion and learning efficiency, grade 5.

Trend: Low cohesion has little relationship to learning but high cohesion is directly related to learning.

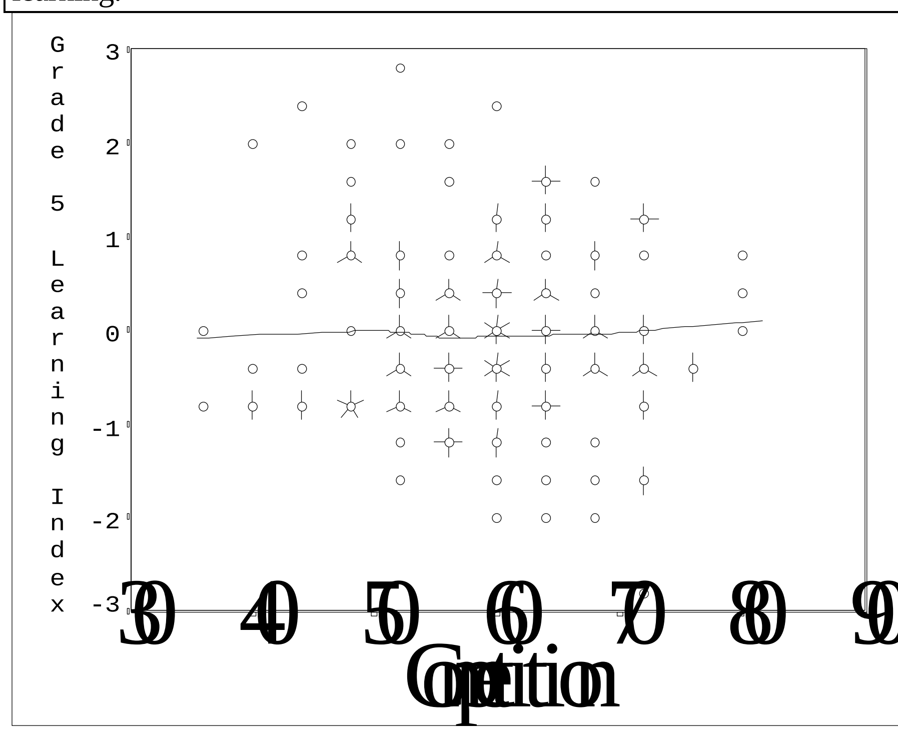

Figure 6. Relationship between competition and learning efficiency, grade 5.

Trend: Within-class competition among students is not related to students learning.

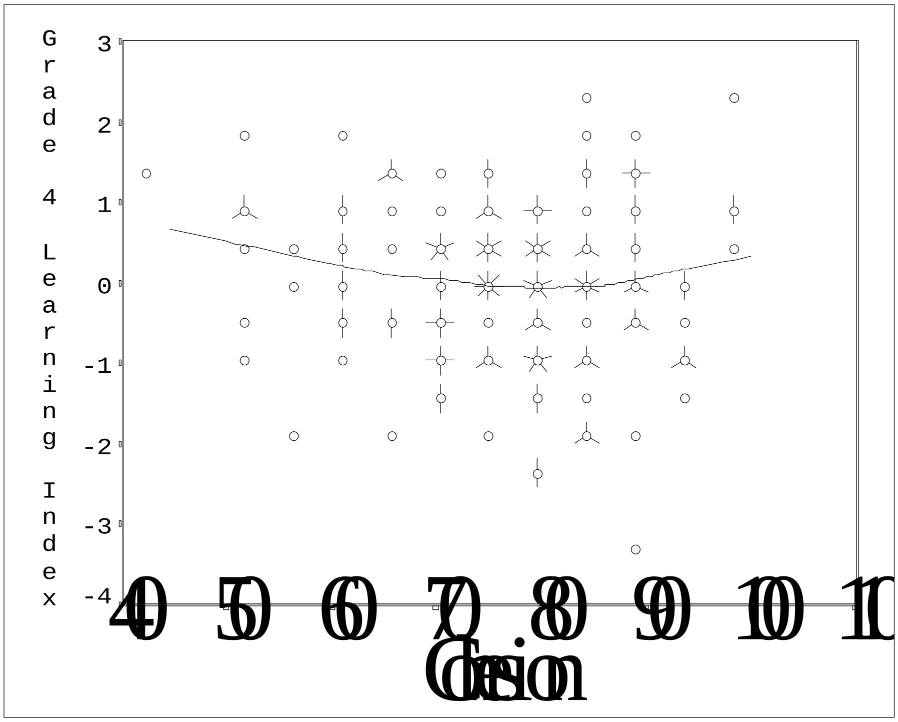

Figure 7. Relationship between cohesion and learning efficiency, grade 4.

Trend: This curvilinear relationship indicates that when, classroom cohesion is low there is a negative relationship between cohesion and learning. When cohesion is high, there is a positive relationship between cohesion and learning.

Summary

Classroom observations showed that students were inundated with worksheets and sample problems to practice for the state test, worked in isolation of each other and seemed very bored. While not part of this study, it is also common knowledge that test scores have shown little growth on nationally normed measures over the past 3 years in this urban district. This study found that high-achieving classes are perceived to have lower friction and to be easy. But, learning can occur in both high- and low-achieving classes. Learning is most effective when (a) satisfaction is high (60+), (b) cohesion is high (80+), and (c) friction is low (<30). Competition and perceptions of difficulty have little or no effect on learning. The implication is that personal growth and self-enhancement are related to the attained level of achievement, but involvement and sharing are necessary for learning at all levels of achievement.

Significance of Study

The current wave of reforms in mathematics and science focus strongly on making learning meaningful and relevant to the student. The results of this study justify this approach. It also shows that many environmental factors assumed to be part of the classroom, like competition and perceptions of difficulty, may be influencing students to a greater extent from outside the classroom. One reasonable inference from this study is that classrooms need to improve student satisfaction with learning. However, the most important aspect of this study is that it may now be possible to obtain more accurate, systematic relationships between actual classroom learning and students' perceptions of the learning environment in very large systems. While further research is needed, it looks as if recent analytical techniques may make it possible to monitor and improve systemic reform efforts using large-scale implementation of classroom learning environment instruments. For example, the system can identify the level of classroom learning efficiency based on a learning environment survey and intervene or emulate long before the final achievement examinations are given. What is not known is whether high learning efficient classrooms as measured by the MCI have practices that relate to the national standards in mathematics and science, or does the Learner Efficiency Index support the traditional realist epistemology.

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