PREDICTING PHYSICS ACHIEVEMENT: A HIERARCHICAL MODEL OF STUDENT PERCEPTIONS, STUDENT BACKGROUNDS, AND SCHOOL CHARACTERISTICS

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Predicting Physics Achievement:

A Hierarchical Model of Student Perceptions, Student Backgrounds, and School Characteristics

by

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Abstract

The purpose of this paper was to develop a model to predict physics achievement. A population of about 1500 students was used to explain approximately 64% of the variance found in high school physics marks. The model was developed using proximal and distal variables derived from an educational productivity theory. The model contains four student background characteristics (context variables), two student perception variables (transactional variables), and five school level variables (context variables) that were arranged and analyzed in a hierarchical fashion. The model supported the idea that proximal variables were more influential in predicting achievement than were distal variables. The model also indicated that student perceptions were important predictors of achievement but they were much less important than the student background characteristics such as prior achievement.

Acknowledgements

I would certainly never have completed this task had it not been for faith in God and the efforts of the following people and organizations. I would like to thank Dr. Robert Crocker for providing such a great deal of effort and guidance in the completion of this project. In addition, I would like to thank The Department of Education of the Government of Newfoundland and Labrador for supplying the data and data forms that were necessary for the analysis. For an understanding that shows maturity beyond their years, I would like to thank my children Shelby and Nicholas. My father, Harry, and mother, Mildred, have supplied continuous and uplifting encouragement for which I am grateful. Above all I would like to thank my wife, Nancy, whose drive and love enabled this project to get completed.

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I. Introduction

The purpose of this research was to develop a hierarchical model that can be used to predict achievement for high school physics students. The model consists of independent variables related to three groups of predictor variables: students' backgrounds, students' perceptions of their quality of school life, and school variables, in addition to the outcome variable-physics achievement. Four conclusions are drawn from this model. First, the major influences on achievement rest mainly with student characteristics as opposed to school characteristics. Second, student-background characteristics are better predictors of achievement than are students' perceptions of their school life as measured by the Quality of School Life Survey (QSL) (Epstein & McPartland, 1976, Williams & Batten, 1981). Third, the magnitude of the student level predictors changes from school to school because they are moderated by school level variables. Fourth, student-backgrounds can be used as predictors of student perceptions.

Research surrounding the development of this model reaffirmed some of the problems inherent in dealing with complex educational data. First, it became apparent from the outset that two levels of data, student and school, were involved in the analysis. Burstein (1980) stated that this type of data is problematic for reasons that stem from aggregation and disaggregation biases. This problem can now be overcome to some degree by the use of hierarchical models (Bryk & Raudenbush, 1992). Another problem was that the student level data gave rise to a causal framework, with student backgrounds influencing the quality of school life as well as achievement. This indicated that some sort of causal modeling was necessary to illustrate findings in this area. Traditionally, this second problem has been handled by path analysis techniques (Schumacker & Lomax, 1996). However, an extensive review of pertinent literature did not reveal a clear method of incorporating both hierarchical analysis and causal analysis. Consequently, a decision had to be made as to which form of analysis was most appropriate for this particular study. It was decided to proceed with a hierarchical analysis to examine school differences in achievement, and to convey the causal influences by showing that there are relationships between student-background variables and the QSL.

Definition of the Problem

Both student and school groups of variables may relate to achievement in several ways. Figure 1 illustrates a relationship in which these groups of variables exert independent but direct influences on achievement. Figure 2 uses a nested design to show how the student group of variables might affect achievement in a more direct fashion than the school group. Factors at the student level, such as student ability and attitude, might be expected to have more impact on learning than a group of factors at the school level such as school size or geographic region. This illustrates the concept of proximal and distal variable distinctions as put forth by Fraser, Walberg, Welch, and Hattie (1987) in a discussion of the educational productivity model. However, student variables can be

Figure 1

Student and School Variables as independent Predictors of Achievement

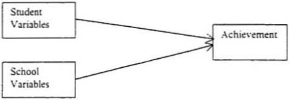
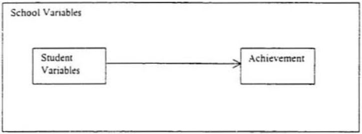


Figure 2

Student Variables Nested Within School Variables as Predictors of Achievement



further subdivided into two categories: student backgrounds and student perceptions. Student backgrounds refer to variables such as gender, ability, and science aptitude. Student perceptions refer to students' attitudes, and feelings regarding their schools, classmates, and teachers as measured by the Quality of School Life Survey.

The relationship between the two student categories, student backgrounds and student perceptions, has at least two possible orientations. The categories could be mutually exclusive as in Figure 3, or the student perceptions could be regarded as being dependent to some extent on the student background subgroup and the school level variables as in Figure 4. The latter arrangement is of the same form as the contextual and transactional variable arrangement put forth by Fraser, et. al. 1987.

Figure 4 illustrates both causal and hierarchical components. Reason dictates that the perception of an upcoming event would affect the outcome of that event. The perception, however, may come from experience with similar past events (Keeves, 1986; Koballa, 1988). This indicates that student backgrounds may have an impact on the QSL and the direction of causation would be from student-backgrounds to QSL to achievement as shown. Figure 4 also incorporates a nested design to illustrate the hierarchical nature of the model being developed. This hierarchical structure arises from the fact that school variables are inherently measured at the school level, whereas student-level variables are measured at the individual level.

The aim of the study was to develop a model that explains the relationships that exist within the framework of the fourth model. Specifically, the purpose was to show how student backgrounds, student perceptions, and school variables could be used

Figure 3

Independent Effects of Student Background Variables, Student Perceptions, and School Variables on Achievement

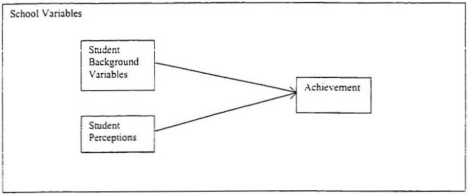
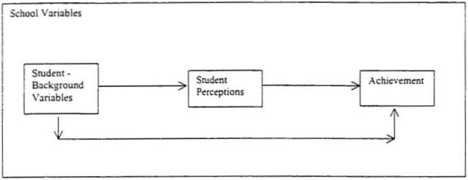


Figure 4

Dependent Structure of Student Background Variables, Student Perceptions, and School Variables



to predict physics achievement. The relationships, shown in Figure 4, are examined by attempting to answer the following broad questions regarding physics achievement in the Province of Newfoundland and Labrador:

1. Can physics achievement be modeled as a hierarchical function of school and student-based variables?
2. Do schools differ in the degree to which student level variables can predict physics achievement?
3. Are students' perceptions of their quality of school life influenced by student background characteristics?

Theoretical Framework

The theoretical constructs of the model developed by this research originate from the educational productivity model developed by Walberg and colleagues (Fraser, et. al., 1987; Wang, Haertal, & Walberg, 1993). Wang, Haertal, and Walberg (1993) used the educational productivity model as an organizational framework for a "knowledge base for school learning" (p.253). Demonstrating that the educational productivity model provides a reasonable framework upon which further research can be established.

In the development of the educational productivity model three key points emerged. First, large numbers of independent variables can be grouped together into one of nine key constructs that influence the dependent variable, achievement (Fraser, et. al., 1987). Second, both contextual (existing independently of the learning behavior) and transactional (existing during the learning behavior) variables influence achievement

(Fraser, et. al., 1987). Third, proximal variables (those closest to the learning behavior) have more influence on achievement than distal variables (those removed from the learning behavior) (Wang, Haertal, & Walberg, 1993).

The educational productivity model is one of the more encompassing models that has been developed to predict student achievement. It uses nine key factors from prior models, meta-analysis of hundreds of studies, and expert ratings of the influence of variables on achievement. These nine factors are grouped into three sets (Fraser et. al. 1987, Reynolds & Walberg, 1991).

Set 1	Student aptitudes	1.	Ability or prior achievement
		2.	Chronological age
		3.	Motivation
Set 2	Instruction	4.	Quantity of instruction
		5.	Quality of instruction
Set 3	Psychological environment	6.	Home environment
		7.	Classroom and school environment
		8.	Peer group environment
		9.	Mass media environment

Within these three sets of factors there exist both contextual and transactional variables (Fraser et. al. 1987). Contextual variables exist prior to any engagement between the student and the learning environment and are unaffected by the learning experience. Examples of this type of variable would be student age, gender or intelligence. Transactional variables exist during the interaction of the student and the learning environment and involve variables related to student attitudes and the classroom environment. Outcome variables involve measures of changed behavior such as increased subject matter knowledge or new attitudes to school. (Fraser et. al. 1987)

The educational productivity model also addresses distinctions between proximal and distal variables (Wang, Haertal, & Walberg, 1993). The authors state that "Distal variables are at least one step removed from the daily learning experiences of most students" (Wang, Haertal, & Walberg ,1993, p.276). Similarly, "proximal variables like psychological, and instructional, and home environment variables have more impact on learning than most variables studied" (Wang, Haertal, & Walberg ,1993, p.276).

The three dimensions of the educational productivity model provide the basic structure used for the model in this study. Variables identified as belonging to one of the nine key constructs are placed into a student and school organization. Student backgrounds and school characteristics are essentially context variables; student perceptions of their school life occur during the learning process and are thus transactional. All the student level variables are regarded as proximal variables and school level variables are regarded as distal variables. The proximal/distal distinction provides a rationale for using hierarchical modeling to predict the outcome variable physics achievement.

Selection of Variables

Variables for this particular study had to be selected from within the constraints of the model and had to be available in databases sufficiently large for stable statistics to be computed. In this case, the primary database was the high school certification system used by the Department of Education in Newfoundland and Labrador and this was supplemented by data from the QSL and the School Profiles and Teacher Certification databases. A review of the literature, knowledge of the educational system of interest, and classroom experiences serve to identify a number of variables within these databases at both the student and school level. These are associated with each of the three groups of variables in the model. These databases were used to construct data files at student (proximal) and school (distal) levels for use in the hierarchical analysis.

Physics achievement was chosen as the outcome variable for two reasons. First, a common measure of achievement is necessary to give a reasonably stable outcome variable. Second, political and economic conditions suggest the need for more emphasis on science education (Crocker, 1989). Consequently, acquiring specific ideas to improve science education, in this case physics education seems very relevant.

This study does not utilize an exhaustive list of factors that could influence achievement. It does, however, utilize some of the contextual and transactional factors present within the student and school variable groupings. In doing so it should be realized that other possible variables which affect achievement, such as family socioeconomic status and community expectations of its children, were omitted because they were either unavailable within the databases or did not fit the school/student orientation of interest in this study.

This does not mean that the omitted variables were unimportant. Indeed, according to Willms (1992), to adequately monitor school achievement, measurements at student, school, community, and policy levels are important elements. However, Willms specified that, "If data on prior achievement or ability are available, measures of SES and other pupil characteristics do not contribute substantially to analyses of school effects" (p.63). Since reasonable measures of student achievement were available for this study, school comparisons can be made in the absence of the student level variables that were unavailable for this analysis.

Population Characteristics

The population consists of all Level III students taking the third level physics course in the province of Newfoundland and Labrador in the 1993-1994 school year. The province's population is small and largely rural, and graduating classes range in size from only one or two students to two or three hundred. High school science classes vary in size from three or four to more than thirty students. School structures vary from community to community. Some rural communities have all grade schools while others separate the primary/elementary grades from the junior/senior high grades. Urban centers of the province sometimes further divide schools into primary, elementary, junior high, and senior high.

Teachers in the system are generally highly qualified with most having at least one Bachelor's Degree in Arts or Science in addition to their Education Degree. However, they are often required to teach subjects outside their field of expertise. In smaller schools a teacher of science may indeed not have a science degree. And it is not uncommon for a science teacher with training in one science to be responsible for the entire science curriculum of a school.

The last three years of secondary school are termed levels I, II, and III (typically referred to as grades 10, 11, and 12). In this three-year system students have course options available to them. However, there is a minimum core requirement of science, math, and language arts courses that must be completed to meet the graduation requirements. Beyond this core group there are wide differences in students' choices of elective courses between the smaller and larger schools. Consequently, the proportion of students taking physics varies substantially from school to school.

Summary

The goal of this research was to use the constructs of the educational productivity model (Wang, Haertal & Walberg, 1993) to predict physics achievement. Data related to students' prior achievement, age, and gender were classified as a student background group and measured at the student level. Data concerned with students' affective domain were regarded as a transactional group and were also measured at the student level. Data such as population, geographic region or teacher qualifications were treated as school level data. Because the data evolved at two levels, a hierarchical approach to data analysis was used.

II. Modeling in Education Research

The starting point of this study was the idea that educational achievement can be modeled as a function of a combination of contextual and transactional variables that are capable of being placed within some sort of hierarchical structure. The literature does reveal that predicting educational achievement from a group of predictor variables is not a new idea. Indeed the educational productivity model, from which the current model was built, was designed specifically to predict achievement. This model was, in turn, based on philosophical, correlational, and causal theories of education. The origins of the educational productivity model are noted briefly here in order to indicate that the model has both theoretical and empirical support.

Theoretical and Empirical Support

In their review of eight models, Haertal, Walberg, and Weinstein (1983) asserted that the educational productivity model has elements of commonality with the theories of Bennett (1978), Bloom (1976), Glaser (1976), Harnischfeger and Wiley (1976), Cooley and Leinhardt (1975), Gagne (1974), Bruner (1966), and Carroll (1963).

Probably the most influential of these was Carroll's time model (Carroll, 1963).

The Carroll model basically claims that a student's success is directly related to the ratio of the time a student spends on a learning task to the time required for the student to succeed at the learning task. Time required is related to aptitude, ability, and quality of instruction. Time spent is a factor of time available and perseverance.

Other theorists have focused on different aspects of learning. Bloom (1976), for example, focused on student motivation and corrective feedback in his mastery learning techniques. Bennet (1978), in his model of the teaching and learning process, discusses intelligence as a key factor in success when measured in terms of prior achievement. Harnisfeger and Wiley (1976) found that teacher qualifications and the amount of time students spent on learning activities to be major factors of student success. Gagne (1976) focused on adjusting curriculum into definable and measurable components, based on the conditions necessary for learning to occur. Glaser (1976) used ideas similar to Gagne's to develop teaching strategies that attempted to span the theoretical and the practical worlds.

Empirical support for the educational productivity model was found by examining literature on the factors influencing achievement. The paper by Wang, Haertal and Walberg (1993), a synthesis of several hundred other syntheses, conceptual theories, and expert opinions, established that the educational productivity model can be used as a primary framework upon which research can be built.

An example of this type of research is a study by Fraser et. al. (1987) in which the educational productivity theory was tested on a sample of 1,955 17-year-old students, 2,025 13-year-old students, and 1,960 9-year-old students. Fraser et. al. concluded that the constructs within the model were accurate predictors of student success. Further these findings supported the idea that proximal variables are better predictors of student success than distal variables. Additional support for the educational productivity theory can be found in the statistical methods section that follows.

Statistical Methods

With the emergence of increasingly complex statistical procedures, mathematical models have proven more successful in making matches between theoretical models and the available data. Some examples of mathematical modeling as it applies to educational research are reviewed in the following subsections.

Linear regression.

Linear regression involves building a linear relationship between a number of independent variables and one dependent variable. The goal of linear regression modeling is to find an optimal set of independent variables, which most accurately predicts the dependent variable (Montgomery & Peck, 1982).

This technique of modeling is widely used in assessing the relationship of achievement to context and transactional variables. For example, Horn and Walberg (1984) used a multiple linear regression technique to model the effects of instruction on achievement and interest. Walberg, Fraser, and Welch (1986) used regression to test educational productivity theory on a population of 17-year-old science students. Kurdek and Sinclair (1988) utilized the method to determine the relation between the independent variables of family factors and gender, and the dependent variables, school achievement and behavior.

Path (causal) analysis.

Path analysis is closely related to linear regression. The major difference is that path analysis is used to identify possible causal relationships between the independent and dependent variables. The coefficients are combinations of direct and indirect effects of the independent variables on the dependent variable.

Examples of causal influences are also found in the literature on student achievement. Parkerson, et. al. (1984) applied path analysis to the educational productivity model and found that the simpler regression model may not be an adequate representation of the model. Schibeci and Riley (1986) used causal modeling in determining the ability of a theoretical model to illustrate the influence of student characteristics on achievement and attitudes.

Reynolds and Walberg (1991) used latent variable constructs with path analysis techniques to again shed light on the utility of the educational productivity model. The result was an acknowledgment by the researchers that the productivity theory could be revised to include links between the constructs of the model.

Hierarchical modeling.

The hierarchical linear model addresses methodological concerns that occur when two or more levels of aggregation exist in the data. These concerns were brought to light in large part due to the work of Burstein (1980). Burstein was concerned with the loss of variance, at the student level, when individual student characteristics are aggregated to something resembling a school average of the characteristic. Similarly, aggregation bias occurs when a school characteristic is used as a constant for every student within the school. These aggregation biases are a consequence of the improper choice of the unit of analysis and result in misestimated precision for some components of the model (Bryk & Raudenbush, 1992; Raudenbush & Bryk, 1986).

Hierarchical modeling is a system of analysis that involves using two or more levels of data. It follows the basic form of the regression equation. However, the coefficients calculated for the level 1 equation (usually student level) are regarded as dependent variables and predicted from second order (usually school or teacher level) equations. This is accomplished by using a nested design in which the students are nested in their own schools. The net result of this is a system of equations that predict both the outcome variable and the strength of the relationship between the outcome variable and the independent variables.

Young (1994) used this method to investigate gender issues. In a report on gender differences in physics achievement, she found that 12% of the variance in physics achievement was due to schools and not to the students. Lee, Croninger, and Smith (1997) demonstrated that the effect of school variables on achievement varies among schools. Similarly, Young, Reynolds, and Walberg (1996) have shown that there are school level variances present within the educational productivity theory.

Identification of Possible Variables

Having established that the educational productivity theory has both a solid theoretical and empirical grounding, it becomes necessary to explore the nature of the variables that can possibly be included within its framework. The variables that are available from the databases being studied must be fit into the rather complex variable structure demonstrated by the model. Variables clustered into one of the nine key constructs have either contextual or transactional characteristics, and furthermore have large and small effects on achievement depending on whether they are proximal or distal in nature. (Fraser et. al., 1987; Wang, Haertal, & Walberg, 1993)

Analysis of the proximal (student) and distal (school) variables, using a hierarchical approach allows us to compare schools when the characteristics of students are controlled for. This is a necessary step according to Willms (1992), who proposed that databases used to compare schools must have an optimal set of variables at several different levels of aggregation, including the student level. The following sections illustrate some of the more generic variables used in the construction of the current model other variables are located specifically in the databases under study and are not illustrated by this literature review.

Gender.

Gender is one of the essential nine variables within the educational productivity model according to Wang, Haertal, and Walberg (1993). Fraser et. al. (1987) reported gender as being a factor in predicting achievement and report correlations of 0.19, 0.16, 0.03, 0.16, and 0.04 between the two as evidence to support the inclusion of gender as part of the educational productivity theory. Willms (1992) identified gender as part of a group of student inputs that need to be controlled in order to compare schools. He reported that measures of prior achievement and gender together account for more than 50% of the variance in primary reading scores, for example.

In addition to being important to the current model, gender differences in science achievement are a concern of science educators (Bulcock, Whitt, & Beebe, 1991). These concerns generally stem from ideas that females do not do as well in science courses as their male counterparts (Koballa, 1988). A review of the literature suggests, however, that the findings supporting this argument are generally correlational in nature with only small correlations being reported. The findings are statistically significant largely because of large sample size. Nevertheless gender differences are regarded as important and are consequently included. The research, reported in the following paragraph, exemplifies some of the results obtained in this area.

Schibeci and Riley (1986), using a sample of 3,135, NAEP 1976-77, 17-year-old students, found a correlation of -0.25 between science achievement and gender. Walberg, Fraser and Welch (1986), using data gathered from the 1981 NAEP results, conducted a second study of 1,955 17-year-old students. They found a correlation of -0.10 between science achievement and gender. Germann (1994), found correlations of -0.26, 0.27 and -0.22 when gender (male=1) correlated with cognitive development, academic ability and biology knowledge respectively. Bulcock, Whitt, and Beebee (1991) found a significant correlation of -0.149 between gender and achievement in grade 10 mathematics.

Prior achievement.

The high correlation of ability and achievement is well known and has been utilized in one form or another in a great number of models by many researchers. According to Wang, Haertal, and Walberg (1993), prior achievement is sometimes seen as equivalent to ability or intelligence. This variable is probably the best predictor of achievement and is thus the cornerstone of the educational productivity model. Willms (1992) asserts that prior achievement is a strong predictor of achievement, so strong in fact that when good measures of prior achievement are used even well known predictors like socio-economic-status contribute very little to reducing the overall variance in achievement. In his view, this is largely due to the fact that socioeconomic status is highly correlated with prior achievement.

Walberg (1984), using a "synthesis of about 3,000 studies" (p.22), found that ability (IQ) was a strong correlate of learning (0.71) and a moderately strong correlate of science learning (0.48). Parkerson, Lomax, Schiller and Walberg (1984), in developing a model of science achievement using data from 882 students, reported a correlation of 0.42 between ability and achievement. Using a LISREL model, a factor weighting of 0.72 was found for prior ability, which was six times the next largest predictor.

Tamir (1987) supports the proposition that prior ability in science is a better predictor of science achievement than is general prior ability. In his study of 2277 grade 12 students who wrote the science test 3M as part of IEA studies, found that science majors do better on general science testing than non-majors regardless of the scientific area. For example, students who studied chemistry in grades 10 or 11 had a mean score of 70.1 on the biology subtest while those who did not study chemistry had a mean score of 64.5 on the same subscale. Crawley and Coe (1990), in their study of 100 students, used both general ability and science ability as predictors of students' intentions to enroll in a high school science course. A correlation of -0.17 was reported between general ability and the intention of a student to enroll in a senior high science course, while the correlation between science ability and intention to enroll was 0.44 (this was for a highly academic group).

Motivation.

Motivation is a key component of success (House 1988). Keeves (1986) claims that "experience and research indicate that the performance of a student at school is influenced by the student's prior performance, by attitudes to specific aspects of school learning and by motivation to learn" (p. 117). Fraser et. al. (1987) report correlations of 0.26 and 0.34 between achievement and achievement motivation. Wang Haertal and Walberg (1993) suggest that "motivational and affective variables, long acknowledged as important by classroom teachers, must be considered as key attributes necessary for developing independent, self regulated learners" (p. 263). Young, Reynolds and Walberg (1996) found a correlation of 0.06 between motivation and achievement in science (significant in this study because of the large sample size). Evidence such as this has prompted Walberg and his colleagues to include motivation as one of the nine factors that consistently predict achievement (Walberg 1984; Reynolds & Walberg 1991).

Transactional Factors

As indicated earlier, transactional factors are those present during the interaction of the student with the learning environment. This group of factors incorporates such ideas as student behavior, teacher behavior, instructional resource exposure, classroom climate, and external intrusions. (Fraser et. al. 1987) It is within this group of factors that the items from the Quality of School Life Survey (QSL) (Epstein & McPartland, 1976, Williams & Batten, 1981) were placed. The QSL, having been measured some five months before the school year ended, would be a measure of such things within the context of the school environment. Willms (1992) states that student attitudes to school are quite different between low and high achieving schools. He also cites the QSL instrument being used in this study as one possible questionnaire that could be used to measure student satisfaction with school life.

It was hypothesized here that student perceptions of school life, as measured by the QSL, were both important outcomes of schooling and also predictors of student achievement. This view was supported by Epstein and McPartland (1976), who stated that "School-effects research and school evaluation have been preoccupied with the measurement of academic achievement"(p. 1). Epstein and McPartland went on to argue that the quality of school life is also an important measure of success. They reported a correlation of 0.14 between the quality of school life and academic achievement using a composite score of the QSL from the scores of students in grades 7, 9 and 12. Fraser et.al. (1987) claimed that school climate is likely to influence students' achievement but little research has been done in the area. According to Johnson and Johnson (1993) "A productive classroom environment should be characterized by students exerting high effort to achieve, positive and supportive relationships among teachers and students and between students and teachers and psychologically healthy and socially competent students" (p.72). Walberg and Reynolds (1991) state that "because the schooling process appears to be a network of effects, gains made on one factor may strengthen the chain of influence on achievement" (p.106).

The QSL is a broad instrument designed to describe how students perceive their environment (Epstein & McPartland 1976, Williams & Batten 1981, Bulcock 1995). The original instrument used by Epstein contained 27 items, organized into a three-factor structure, and focused on the primary and elementary grades. Williams and Batten and later Bulcock increased the number of items. Subsequent factor analyses have shown the presence of more than three factors. Detailed reliability and validity checks of the different versions of the QSL were conducted by Epstein and McPartland (1976), Bulcock (1995), and Johnson and Johnson (1993).

Although little was found in the literature concerning the relationship between QSL scores and student achievement, there is a great deal of research that reports on various aspects of learning environments and achievement. This research may be used to provide support for using the QSL instrument as a predictor of achievement. For example Schibeci and Riley (1986) utilized student perceptions of teacher support, teacher enthusiasm, usefulness of class, and enjoyment as they applied to science class These perceptions were found to have correlations of 0.11, 0.10, 0.25 and 0.22 respectively with student achievement. The QSL instrument does not measure these items for a particular course or teacher but rather for the school as a whole. This study is particularly interesting in that it reports a direction of causation stating that perceptions influence attitude, which in turn influence achievement.

Walberg's productivity model also has components that may be identified with parts of the QSL. Specific scales within the QSL represent general concepts in the productivity model, such as students' attitudes toward teachers, students' motivation, and class environment. Walberg's concept of motivation, for example, may relate to the opportunity to learn scale on the QSL (the opportunity-to-learn scale being defined as a measure of how pleased students are with their work). The concept of attitude to teacher may parallel the QSL factor of students' perceptions of teachers. The attitude criteria may possibly correspond to the school usefulness factor on the QSL. In addition, class environment may relate to student satisfaction, student dissatisfaction, and the extent to which the student identifies with school (Walberg 1984, Horn & Walberg 1984, Fraser et. al. 1987, Reynolds & Walberg 1991, Young, Reynolds & Walberg 1996).

School Variables

School variables come from a wide spectrum of possible influences on achievement. Traditionally, studies dealing with school variables and student achievement have had to use data aggregation or disaggregation. As already discussed, inferences drawn from studies in which inappropriate levels of aggregation are used may or may not fully describe the relationships being studied.

Willms (1992) suggests that hierarchical analysis should be used any time there is an attempt to compare student achievement in multiple schools. He claimed that effective school monitoring should include variables that pertain to school policies, practices, and characteristics. These groups might include such items as instructional leadership, disciplinary climate, and school streaming practices. Raudenbush and Bryk (1986) argued that much educational research deals with hierarchical data. In particular they claim that statistics that report relationships between two differing levels can give misleading results. In a test of their hierarchical linear model, on previously analyzed

High School and Beyond data, their preliminary results suggest that the single level analysis of the original studies does not convey the full scope of the interactions.

Realizing the difficulty of dealing with multiple levels of data, Young, Reynolds and Walberg (1996) utilized a hierarchical analysis technique to identify school and student level effects on achievement. The authors report that student level data account for 75% of the variance between the schools, leaving only 25% of the variance being attributed to the actual differences between schools. This illustrates the need for the inclusion of student level variation when looking at the effects of school variables on student achievement.

Research on school effects without a hierarchical basis also provides some possible variables to be included within school level data. Fraser et. al. (1987) identifies items such as teacher experience and amount of science study as possible determinants of student achievement. Fraser and his colleagues reported, however, that these teacher characteristics appear to have little impact on student achievement.

According to Good and Brophy (1986), some schools are more effective than others. The authors discuss nine characteristics of effective schools. Two of these were staff stability and staff development. These same authors, however, did not attribute school effectiveness to physical school attributes. These results were based on the average outcome of the school as opposed to specific student outcome. Harnish (1987) used school averages with school level variables in a study that reported on school effectiveness. In this sample of 800 schools and 18,684 students, the correlations reported between school size, student teacher ratio, teacher turnover, and the percentage of graduate degrees with average composite school achievement were 0.13, -0.01, -0.11, and 0.15, respectively. These studies both illustrate aggregation of data that might have led to incomplete results because of the multiple levels of data involved.

Summary

The literature review explains a number of key points relevant to the variables and the model used in the study. First, theoretical and empirical bases were identified for the educational productivity model. Second, specific statistical methods appropriate to modeling school achievement were described, with hierarchical models being considered most suitable when data at more than one level of aggregation exists. Third, specific variables were identified in the literature as having possible effects on student achievement. These variables appear to fit into one of the three key elements; student background variables, variables dealing with student perceptions, and school variables, examined within the model.

III. Methodology

This chapter focuses on the specific nature of four key aspects of the study. First, the characteristics of the student-population are examined and the specifics of how these population characteristics may influence the selected variables are clarified. Second, the specific variables used in the study are presented. Third, the hierarchical structure used to analyze the proposed model is developed. Fourth, the procedure for the data analysis is presented.

Population Characteristics

The current study utilizes the full population of level III students who completed the QSL in February of 1994 and the senior physics course in that same year (n = 1,529). This amounts to approximately 20% of the level III student body. The nature of how variables are fitted to this student population needs to be established in terms of where the variables come from, restrictions that are imposed by the make-up of the school system, and the nature of instruments used to collect information.

Sources of data.

The databases maintained by the Department of Education contain the relevant data for all aspects of the study. The outcome variable, physics achievement, was obtained from the high school certification database as was information concerning student background variables. Similarly, the data on school characteristics was obtained from the school profiles database. Many of the variables considered in this study were created from numerical data held in these databases, while some variables such as gender did not have to be created, but rather coded for use with the HLM/2L computer program (Bryk, Raudenbush & Congdon, 1996). The variable gender, for example, was coded from male and female into a dummy variable that recorded male =1 and female =0.

Restrictions from within the database.

As indicated previously, the backgrounds of the students were quite diverse and this may have some influence on the chosen variables. For example, some smaller schools offered choice only between sciences while larger schools might have offered a choice between sciences and other disciplines. Similarly, some schools offered either the advanced or academic mathematics courses while other schools offered both. In effect, this means that for some schools a variable will vary considerably within the student body but for other schools the variable may be a constant for every student. This difference will likely be responsible for a lack of variation within some of the variables, which causes problems in the analysis because there is no way to compute the statistics for a variable when it is a constant in a particular school.

Physics achievement.

The grading system, which eventually determined the outcome variable, may or may not have been consistent across the province. In past years, a public examination program, which provided a standardized exam and a standard marking scheme, had been in existence for the level three students. However, for the 1994 population of students there was no standard final exam available, due in part to labor disputes between the province's teachers and the Department of Education. This is not as problematic as it may seem since correlations between public exam marks and year-end marks are very high. For example, in the years 1992, 1993, and 1995 correlations of 0.76, 0.74, and 0.73 respectively are reported. These correlations were based on populations of 2,682, 2,855, and 3,420 grade 11 and 12 students (Crocker, 1998). These correlations provide a relatively high level of concurrent validity. While not being a great problem statistically, lack of a standardized grading system does imply that any differences between schools, reported by the hierarchical analysis, would contain two items, the actual differences between schools and differences in teacher grading from school to school.

The quality of school life survey.

The Department of Education used the Quality of School Life survey (QSL) to gather data on student perceptions of school life. This 45-item assessment instrument was to be written by all grade 12 students in the province of Newfoundland and Labrador in February of 1994. Of the 7,645 students who completed the instrument, only 7,032 had data that could be matched with the other databases. The response categories for the QSL instrument were:

1 strongly agree
2 agree
3 disagree
4 strongly disagree.

The response categories were reversed for those items with reverse polarity so that positive responses always had higher rankings than negative responses.

The Department of Education subdivided the scale into seven different factors: student satisfaction, student dissatisfaction, opportunity to learn, the extent to which school is perceived as being useful, the extent to which the student identifies with school, the students' perception of their own status within the school, and the students' perception of their teachers. While the existence of factors within the QSL was not in question, the exact number seemed to change. Nimmer (1979) claimed "further studies.... must be completed to expand and establish meaningful norms for all grade levels in which the QSL may be used" (p.223). Nimmer's advice seems to have been followed by several researchers. Williams and Batten (1981) identified a six-factor structure for the population of students they were studying. However, Bulcock (1995) identified a five-factor structure in his study. One possible explanation for these shifts is that the number of items used is different in different studies. A second explanation is that the structure may be different for different student populations.

A confirmatory factor analysis was conducted in this study to help identify a factor structure for this specific version of the QSL and for the students within the population under study. This factor analysis is based on the whole population (n=7,645) of level III students who wrote the QSL in 1994 using the seven factor structure defined by the Department of Education as the target matrix.

Selection and Measurement of Variables

The variables in this study were selected on the basis of their fit to the model, their use in the literature and their direct relevance to the problem at hand. Initially, this resulted in five student background variables, seven factors of the QSL, the outcome variable, physics achievement, and 23 school level variables. Tables 1 and 2 provide a complete listing of the student and school variables respectively and the coding method for each. It should be noted that these tables represent raw scores and that the variables were standardized for the actual modeling procedure. The advantage that standardization provides is to put all coefficient values on the same scale avoiding the necessity of returning to these tables to interpret the results.

Table 1.

Student Level Variables and Coding Method.

Category	Variable	Variable description	Coding method
Outcome			
	Phyach	Student achievement in physics	Final school grade in physics
Student Background			
	Gender	Gender	Male = 1 Female = 0
	Math	Math 3201	Yes = 1 No = 0
	Numscie	Number of Science Credits	Numeric
	Priorach	Average student Mark in Grade 11	Mean score of a students marks in level 2 (Based on all the courses that they completed in level 2)
	Priorsci	Average student mark in senior high sciences	Mean score of a students marks in high school sciences (Grade 10 and 11 only)
Quality of School Life Factors			
	Satis	Student satisfaction	Mean score of the items that load on the respective factors
	Dissatis	Student dissatisfaction	
	Opptolea	Opportunity to learn	
	Usefulness	Extent to which school is useful	
	Identit	Extent to which a student identifies wth school	
	Status	Students perception of their own status within the school	
	Percteac	Students' perceptions of teachers	

Table 2.

School Level Variables and Coding Method.

Variable abbreviation	Variable description	Coding method
SchoolSize	Number of students in the school	Ln(number of students)[1]
K_12Sch	All grade school	Yes = 1 No = 0
Jun_SenSch	Junior - Senior high school	Yes = 1 No = 0
HighSch	Senior High School	Yes = 1 No = 0
B.Sc.	The number of science degrees held by teachers within the school.	Number of degrees divided by the student population
Master	The number of masters degrees held by teachers within a school	Number of degrees divided by the student populations
PriSci	Class mark for prior science achievement	The mean achievement score for all students in a class on their grade 10 and 11 science courses
PriAch	Class mark for prior achievement	Mean achievement score for all students in a class based on grade 11 marks for all courses.
Partici	Participation rate of teachers within a school regarding extracurricular activities.	Average number of hours a week
Fteptr	Full time equivalent pupil teacher ratio	Ratio of full time teachers to full time students in a school.
Parttea	Part-time teachers in a school	Proportion of part-time teachers in a school.
Satis	Satisfaction factor of the QSL	School's average score on the factor
Status	Status factor in the QSL	School's average score on the factor
Percept	Perception-of-teachers factor in the QSL	School's average score on the factor
Identit	Identity factor in the QSL	School's average score on the factor
Useful	Usefulness factor in the QSL	School's average score on the factor
Dissatis	Dissatisfaction factor of the QSL	School's average score on the factor
Opptolea	Opportunity to learn factor of the QSL	School's average score on the factor
Science	Course teacher has degree in physics	Yes = 1 No = 0
Masters	Course teacher has a graduate degree	Yes = 1 No = 0
Malete	Course teacher is male	Yes = 1 No = 0
SameSch	Whether the course teacher was in the same school the previous year.	Yes = 1 No = 0
Experien	Course teacher experience.	Number of years of experience for the teacher teaching the course.

[1] The ln function is used to reduce the skewness of the actual distribution of school size.

Hierarchical Analysis

The hierarchical model, used to predict achievement, consists of regression equations at two levels, school and student. The level 1 equations have the student level variables centered on the group (school) means. The level 2 equations have the variables centered on the grand (provincial) mean. This method of centering is used so that an individual student is compared relative to other students in his or her school and the individual schools are compared to other schools in the province, this keeps the units of analysis consistent. At level 1(student) the outcome for an individual is predicted by an equation of the form

$$Y_{ij} = \beta_{0j} + \beta_{qj} \text{ (Student Predictor q)}_{ij} + \ldots + r_{ij}.$$

where

Y_{ij} is the dependent variable (e.g., predicted achievement in physics.),

β_{0j} is the intercept (e.g., mean predicted achievement of all students in school j).

β_{qj} is the slope (signifies the relation between a predictor variable and the dependent variable, which controls for the other independent variables), and

r_{ij} is the residual associated with β_{oj}.

The level 2 (school) equations are based on predicting the intercepts (β_{0j}) and the slopes ($\beta_{1j}, \beta_{2j} \ldots \beta_{qj}$). They are typically of the form

$$\beta_{0j} = \gamma_{00} + \gamma_{0q} \text{ (School Predictor q)}_j + \ldots + u_{0j}$$

$$\beta_{1j} = \gamma_{10} + \gamma_{1q} \text{ (School Predictor q)}_j + \ldots + u_{1j}.$$

where

γ_{00} is the grand mean of physics achievement,

γ_{10} is the average slope defined by the variable attached to β_{1j},

γ_{0q} is the slope associated with the school level variable q,

γ_{1q} is the slope associated with the school level variable q and the average student level variable 1.

u_{0j} is the residual associated with γ_{00} associated with individual schools, and

u_{1j} is the residual associated with γ_{10} by school.

The exact nature of the models will be better depicted later in the next chapter as specific hypotheses are tested.

Data Analysis

The data analysis was divided into four distinct sections. The first section deals with the confirmatory factor analysis of the QSL. The second reduces the number of variables down to a more manageable group using preliminary hierarchical analysis in paring attempts. The third stage compiles the selected variables into a model that can be analyzed in terms of its predictive ability and the amount of variance that it can account for. The fourth portion of the analysis determines whether or not the scores on the QSL factors can be predicted by the student background variables.

The first stage of data analysis is a confirmatory factor analysis of the QSL. The factor analysis was completed using structural equation models as depicted by the Amos computer program (Arbuckle, 1997). This analysis would determine whether or not the seven categories (student satisfaction, student dissatisfaction, opportunity to learn, extent to which school is useful, extent to which students identify with school, students' perception of their status within the school, students' perceptions of teachers) used by the Department of Education appear specifically in the grade 12 data. This helped in judging whether or not these specific factors can be used with the grade 12 population.

The student and school level data files were used as the starting point for the second stage of the analysis. First, the analysis focuses on determining the student level predictor variables that significantly reduced the variance in student achievement. In this procedure all possible student level variables were entered into the level 1 equation without any school level variables in the level 2 equations and the significant student level predictors were noted.

The equations used to select the student level variables are

Level 1 $\quad Phyach_{ij} = \beta_{0j} + \beta_{1j}(X_1)_{ij} + \beta_{qj}(X_q)_{ij} + \ldots + r_{ij}$

Level 2 $\quad \beta_{0j} = \gamma_{00} + u_{0j}$

$\beta_{1j} = \gamma_{00} + u_{1j}$

$\beta_{qj} = \gamma_{00} + u_{qj}$

(With X_1 and X_q being used to represent all twelve student level predictors)

This became problematic since when all student level variables were entered together, many schools were "lost" by the computer program. With many schools being discounted by the computer program itself, the results of the analysis may or may not be consistent across all schools. Consequently, a variable may be discounted based on only a few schools but it might have been significant if all schools were included in the analysis. The problem it appears is that small schools do not have enough group variance to support analysis for large numbers of variables.

In order to ensure that variables were not excluded in error, each variable that loaded at an insignificant level was tested again with only prior achievement as an additional predictor. This allowed for many more schools to be included in the decision to omit variables. Prior achievement was used because it was expected to include effects of other variables from previous years (Willms, 1992). By using this in combination with each of the other variables it was possible to determine if these other variables added any new explanatory power in determining achievement above that which would be expected by prior achievement alone. This, consequently, provided additional support for excluding some of the student level variables, in addition to being important in preventing errors that might have occurred in the original selection process because of the loss of schools. The selection of choosing student-level variables to move into the modeling process was based on both techniques.

The equations used to ensure that there was no error made in the selection of the student level variables are:

Level 1 $\quad Phyach_{ij} = \beta_{0j} + \beta_{1j}(Priorach)_{ij} + \beta_{qj}(X_q)_{ij} + r_{ij}$

Level 2 $\quad \beta_{0j} = \gamma_{00} + u_{0j}$

$\beta_{1j} = \gamma_{00} + u_{1j}$

$\beta_{qj} = \gamma_{00} + u_{qj}$

(The X_q notation is used to signify all the statistically insignificant student level predictor variables from the original analysis being analyzed one at a time.)

The second portion of data reduction dealt with the school level variables. In this procedure all school level variables were entered into a base equation on the β_{0j} coefficient and again the significant variables were noted. This procedure was repeated for each of the significant student level variables. Entering all school level variables at the same time on all student level predictors would reduce the number of schools. For this reason student level predictors were treated separately for the preliminary analysis, resulting in a high number of schools being used in the decision-making purposes. This process was repeated for each of the coefficients (β's) of the significant student level predictors. Equations of the form:

$\text{Phyach}_{ij} = \beta_{0j} + r_{ij}$, at level 1and

$\beta_{0j} = \gamma_{00} + \gamma_{1j}(\text{School Predictor 1})_j + \ldots + \gamma_{qj}\ (\text{School Predictor q})_j \ldots + u_{0j}$, at level 2

are used to determine significant school variables for predicting β_0. Equations of the form:

$\text{Phyach}_{ij} = \beta_{0j} + \beta_{1j}(\text{Student Predictor q}) + r_{ij}$, at level 1and

$\beta_{0j} = \gamma_{00} + u_{0j}$,and

$\beta_{1j} = \gamma_{10} + \gamma_{11}(\text{School Predictor 1})_j + \ldots \gamma_{1q}(\text{School Predictor q})_j \ldots + u_{1j}$ at level 2 are used to determine significant school variables for predicting β_1 for each of the student level variables.

In the third stage of the analysis, the significant variables from both the student and school initial trials were grouped into a single model with several different explanatory equations used to predict achievement in physics. These equations are specified in their entirety in the analysis sections and are not illustrated at this point. The resulting model was then compared to an unrestricted model through a comparison of variances accounted for by student and school levels of data. This comparison provides some insight into the model's predictive power. The unconditional model is represented as:

$\text{Phyach}_{ij} = \beta_{0j} + r_{ij}$ at level one and

$\beta_{0j} = \gamma_{00} + u_{ij}$ at level 2.

where $Phyach_{ij}$ is the outcome variable physics achievement.

The last stage of the analysis was to determine whether there was a possible two stage causal influence within the model. In order to examine this possibility, the QSL factors were treated as outcome variables and the student background characteristics were used as predictor variables. In this section only the QSL factors that were influential in predicting achievement were analyzed. The equations resemble the following:

Level 1 $\quad QSL1_{ij} = \beta_{0j} + \beta_{1j}(X_1)_{ij} + ... + r_{ij}$

Level 2 $\quad \beta_{0j} = \gamma_{00} + u_{0j}$

$\beta_{1j} = \gamma_{01} + u_{01}$

It should be stated clearly that the intent of predicting aspects of the QSL with student level data was not to do a complete school analysis, but rather to show that the possibility of a causal influence within the student level data exists. As suggested earlier, it is not necessary to analyze the QSL with hierarchical analysis but it is in keeping with the rest of the study.

Summary

A sample of 1529 students from 101 schools was used in a hierarchical model that predicts achievement. Five student background variables, seven student perception variables and 23 school level variables were identified. Provisions for including variables in the final model were made based on a confirmatory factor analysis of the QSL and testing the significance levels of each variable in order to determine their function in the model. The analysis, which follows, focused on two areas. First, it dealt with predicting achievement from all three of the above groups. Second, the analysis treated any significant QSL factors as outcome variables in one section of the study so that a possible casual model could be inferred from the data.

IV. The Analysis

The analysis presented in this chapter is separated into four distinct parts. The first stage is devoted to selecting from the possible variables those that may have a role in the final model. The second section is designed to determine the best possible model from the data. The third section is used to establish the proportions of variance explained by the model. The last section is devoted to illustrating that student backgrounds can be used as predictors of the QSL factors as well as achievement.

Data Reduction

As indicated in previous sections, large numbers of variables were under consideration for this study. Consequently, part of the analysis dealt with reducing the number of these variables to a manageable group. First, a confirmatory factor analysis was completed to determine whether the seven-factor QSL structure used by the Department of Education was appropriate for the population of grade 12 students being studied. The original format of the QSL can be seen in Table 3. The confirmatory factor analysis is felt to be adequate both to reduce the 45 items to a smaller number of factors as well as determine whether the Department of Education's seven-factor structure would hold for the specific population under study.

The results of a confirmatory factor analysis are presented in Table 3. These results (high critical ratios for each standardized regression weight and good reliability measures for each factor) indicate that the 7-factor structure as determined by the Department of Education was a reasonable representation of the QSL instrument. Consequently, the subsequent analysis uses each of the seven factors as independent predictors of achievement. The numerical value of these factors was calculated using the mean score of all items that loaded onto the corresponding factor.

Descriptive statistics for the student, including the seven factors of the QSL and school level data sets are listed in Tables 4 and 5. The data sets provide a total of 13 student variables and 23 school variables, each of which are listed in raw score format. However, for analysis purposes all variables have been standardized for ease of comparison.

Table 3

Quality of School Life Survey: Confirmatory Factor Analysis with Standardized Regression Weights and Cronbach Alpha Reliabilities

Item Number and Description (School is a place where)	Alpha	Standardized Regression weights	Critical Ratios
QSL Factor - Student Satisfaction	**0.87**		
1. I like to be.		0.69	274.12
8. I get enjoyment.		0.68	264.06
15. I feel great.		0.72	283.36
22. I really like to go.		0.76	269.68
29. Learning is a lot of fun.		0.64	261.12
36. I feel happy.		0.69	247.75
43. I feel proud to be a student.		0.67	228.22
QSL Factor - Student Dissatisfaction	**0.71**		
2. I feel restless.		0.53	276.96
9. There is nothing exciting to do.		0.61	256.92
16. I feel bored.		0.66	233.06
23. I feel sad.		0.48	383.27
30. I feel lonely.		0.40	374.66
37. I get upset.		0.41	309.08
44. You are bossed around too much.		0.41	291.67
QSL Factor - Opportunity to Learn	**0.79**		
3. I am happy with how well I do.		0.53	234.50
10. I know the sorts of things that I can do well.		0.45	228.39
17. I know how to cope with work.		0.56	270.84
24. I get satisfaction from the work I do.		0.70	263.59
31. I feel good about my work.		0.73	272.27
38. I can handle my schoolwork.		0.55	253.08
45. The work I do is important to me.		0.62	205.08
QSL Factor - Students Perception of the Usefulness of School	**0.74**		
4. I like to learn new things.		0.52	220.41
11. I find my work interesting.		0.72	292.96
18. I like all my subjects.		0.60	275.00
25. I am genuinely interested in the work I do.		0.73	272.80
32. I learn the things I need to know.		0.48	232.62
39. My friends and I get together on our own to talk about what we have learned in class.		0.43	333.63

Table 3 Continued

QSL Factor - Extent to Which a Student Identifies with School	**0.50**		
5. I learn to get along with other people.		0.57	213.68
12. I can get along with most of the students even though they may not be my friends.		0.58	220.61
19. I have lots of friends.		0.54	213.57
26. Having different kinds of students in my class helps me get along with others.		0.63	216.31
33. You have to get along even with students you don't like.		0.28	230.08
40. I sometimes wish I were different than I am.		-0.05	232.46
QSL Factor - Students Perception of their Status within the School	**0.76**		
6. I know that people think a lot of me.		0.55	260.35
13. People come to me for help.		0.55	265.83
20. I feel important.		0.68	248.49
21. People credit me for what I can do.		0.64	258.75
34. Teachers ask me to help out.		0.54	258.75
41. People think I can do a lot of things.		0.56	248.91
QSL Factor - Students' Perceptions of Teachers	**0.83**		
7. Teachers treat me fairly in class.		0.71	225.06
14. Teachers listen to what I have to say.		0.70	238.85
21. Teachers are usually fair.		0.70	239.09
28. Teachers give me the marks I deserve.		0.60	230.66
35. Teachers help me do my best.		0.64	239.02
42. I like my teachers.		0.66	254.93

Table 4

Descriptive Statistics for the Student Level Variables

Variable	N	Mean	Std. Deviation
Phyach	1529	72.81	13.06
Priorach	1529	76.96	9.76
Priorsci	1529	73.60	11.77
Gender	1487	0.53	0.50
Math	1529	0.56	0.50
Numscie	1529	5.16	1.00
Satis	1529	2.35	0.54
Dissatis	1529	2.82	0.39
Opptolea	1529	2.09	0.38
Usefulness	1529	2.35	0.49
Identit	1529	2.04	0.40
Status	1529	2.29	0.51
Percetea	1528	1.96	0.49

Table 5

Descriptive Statistics for the School Level Data[1]

Variable abbreviation	Mean	Standard Deviation
SchoolSize	3.89	0.8
K_12Sch	0.28	0.4
Jun_SenSch	0.41	0.4
HighSch	0.30	0.4
B.Sc.	2.06	1.9
Master	0.06	0.3
PriSci	73.7	6.0
PriAch	77.02	4.5
Partici	0.43	0.2
Fteptr	15.00	2.2
Parttea	0.03	0.0
Satis	2.43	0.2
Status	2.41	0.1
Percept	2.04	0.1
Identit	2.05	0.1
Useful	2.40	0.1
Dissatis	2.93	0.1
Opptolea	2.05	0.1
Science	0.67	0.5
Masters	0.06	0.3
Malete	0.65	0.1
SameSch	0.85	0.0
Experien	16.61	8.25

[1] Based on 101 schools in the sample.

Student level indicators.

The next step in this process was to include all 12 student level predictor variables in an equation that predicts physics achievement in the absence of any school level data. The results of the analysis yielded significance levels for individual variables that were used to determine which variables would be included in the next stage of the analysis. The selection process reduced the number of variables by carrying only those that were significant predictors at $p<0.10$ forward to the next stage of analysis. The equations used in this procedure at level 1 are:

$$\text{Phyach}_{i,j} = \beta_{0j} + \beta_{1j}(\text{Dissatis})_{i,j} + \beta_{2j}(\text{Percteac})_{i,j} + \beta_{3j}(\text{Satis})_{i,j} + \beta_{4j}(\text{Gender})_{i,j} + \beta_{5j}(\text{Math})_{i,j} + \beta_{6j}(\text{Numscie})_{i,j} + \beta_{7j}(\text{Opptolea})_{i,j} + \beta_{8j}(\text{Priorach})_{i,j} + \beta_{9j}(\text{Priorsci})_{i,j} + \beta_{10j}(\text{Status})_{i,j} + \beta_{11j}(\text{Identit})_{i,j} + \beta_{1j}(\text{Useful})_{i,j}\, r_{i,j},$$

and at level 2

$$\beta_{0j}=\gamma_{0,0} + u_{0j},\ \beta_{1j}=\gamma_{1,0} + u_{1j},\ \beta_{2j}=\gamma_{2,0} + u_{2j},\ \beta_{3j}=\gamma_{3,0} + u_{3j},\ \beta_{4j}=\gamma_{4,0} + u_{4j},\ \beta_{5j}=\gamma_{5,0} + u_{5j},\ \beta_{6j}=\gamma_{6,0} + u_{6j},\ \beta_{7j}=\gamma_{7,0} + u_{7j},\ \beta_{8j}=\gamma_{8,0} + u_{8j},\ \beta_{9j}=\gamma_{9,0} + u_{9j},,\ \beta_{10j}=\gamma_{10,0} + u_{10j},\ \beta_{11j}=\gamma_{11,0} + u_{11j} \text{ and } \beta_{12j}=\gamma_{12,0} + u_{12j}.$$

As illustrated in Table 6, only 6 of the 12 original student level variables have coefficients that are significant at $p<0.10$ for the fixed effects. These results, however, were obtained from only 38 of the original 101 schools that had enough data to make the calculation.

The loss of schools here is due to the small number of students that were located in some schools. With twelve variables in the equation, the computer program did not find enough variance within schools with a few students to compute the statistics. To ensure that no significant predictor was discarded for this reason, a secondary test was used. Each of the insignificant variables was used to predict achievement in the presence of prior achievement. The proportion of variance reduction due to each of these variables, in this secondary test, is recorded in Table 7. This secondary test showed no reason for the results found in the original analysis to be questioned.

The only variable which might possibly be considered for inclusion in the model based on this test procedure is the number of science courses a student had taken, which explained 5.0% more variance than did prior achievement alone. However, this variable caused a much bigger reduction in the number of schools than did any other, from 101 to 76. The reason for this appeared to be that many schools did not offer a substantial number of science courses from which students can chose. This variable was dropped because of a lack of adequate variance.

Table 6

Student Level Effects

Variable	Coefficient	Standard Error	Significance
Priorach	0.22	0.05	0.00
Priorsci	0.47	0.05	0.00
Gender	0.09	0.02	0.00
Math	0.17	0.03	0.00
Numscie	0.04	0.03	0.12
Satis	-0.03	0.03	0.30
Dissatis	0.01	0.02	0.59
Opptolea	0.09	0.03	0.00
Usefulness	-0.03	0.03	0.67
Identit	-0.03	0.02	0.07
Status	0.02	0.02	0.55
Percetea	0.01	0.02	0.66

Table 7

Percentage of Additional Variance Explained by the Nonsignificant Variables in the Presence of Prior Achievement

Variable	Percentage of additional variance	Number of schools out of 101
Numscie	5.0	76
Satis	1.0	93
Dissatis	0.8	93
Usefulness	0.9	93
Status	1.0	93
Percetea	1.1	93

School level indicators.

The impacts of the school level variables in this study were investigated to determine if they had any effects on the student level predictors of achievement. In order to identify possible school level predictors, while preserving as many schools as possible, each student level variable was treated independently of the others. For this analysis, it was not expected that the same school level variable would have a common influence on all student level slopes. Indeed, it was expected that a range of variables at the school level would be involved here. In this analysis, the student level predictors were centered on the group mean and the school level variables centered on the grand mean. The equations used to model the impacts of the school level data are represented at level 1 by:

$$\text{Phyach}_{ij} = \beta_{0j} + r_{ij} ,$$

and at level 2 by :

$$\beta_{0j} = \gamma_{0,0} + \gamma_{0,1} (\text{School1})_j + \ldots + \gamma_{0,q} (\text{School q})_j + \ldots + u_{0j} ,$$

when predicting the intercept, β_{0j}. The level 1 equation

$$\text{Phyach}_{ij} = \beta_{0j} + \beta_{1j} (X_1)_{ij} + r_{ij} ,$$

and level 2 equations

$$\beta_{0j} = \gamma_{0,0} + u_{0j} ,$$
$$\beta_{1j} = \gamma_{1,0} + \gamma_{1,1} (\text{School1})_j + \ldots + \gamma_{1,q} (\text{School q})_j + \ldots + u_{1j} ,$$

are used when predicting the slopes with a different analysis used for each successive student level variable (X_1). (Please note that these equations are very long and tedious and are not included here at full length.)

The results of the analysis of these equations are reported in Table 8. The results show that all but one student level predictor, Identit, have some possible school level predictors.

Table 8

Possible School Level Predictors

Student Level Predictor	School level Predictor	Coefficient	Significance	Number of Schools
Intercept $\beta_{0,0}$				101
	PriAch	0.23	0.00	
	Satis	-0.20	0.07	
	Science	0.12	0.00	
Priorach				93
	Identit	0.18	0.02	
	PriAch	0.21	0.02	
Priorsci				93
	Identit	0.01	0.02	
	Satis	-0.02	0.03	
Gender				89
	Experien	-0.06	0.03	
	Parttea	0.06	0.04	
	Partici	0.11	0.02	
	SchoolSize	0.15	0.04	
Math				81
	Experien	0.10	0.00	
	Opptolea	-0.10	0.04	
	PriAch	0.13	0.02	
Opptolea				93
	PriAch	-0.11	0.32	
Identit				93

Building the Model

The goal of the preceding analysis was to reduce the number of variables that were held within the databases to a feasible number. The analysis that follows illustrates a composite model of both the student and school level variables that had significant impacts in the initial phases. This new model is a form of what Bryk and Raudenbush (1992) refer to as "an intercept and slopes as outcomes model" (p.110) analysis.

The student level equation resulting from the preceding analysis is represented as:

$$\text{Phyach}_{i,j} = \beta_{0j} + \beta_{1j}(\text{Priorach})_{i,j} + \beta_{2j}(\text{Priorsci})_{i,j} + \beta_{3j}(\text{Gender})_{i,j} + \beta_{4j}(\text{Math})_{i,j} + \beta_{5j}(\text{Opptolea})_{i,j} + \beta_{6j}(\text{Identit})_{i,j} + r_{i,j}$$

with the school level equations being

$$\beta_{0j} = \gamma_{0.0} + \gamma_{0.1}(\text{Science})_j + \gamma_{0.2}(\text{PriAch})_j + \gamma_{0.3}(\text{Satis})_j + u_{0j},$$
$$\beta_{1j} = \gamma_{1.0} + \gamma_{1.1}(\text{Identit})_j + \gamma_{1.2}(\text{PriAch})_j + u_{1j},$$
$$\beta_{2j} = \gamma_{2.0} + \gamma_{2.1}(\text{Identit})_j + \gamma_{2.2}(\text{Satis})_j + u_{2j},$$
$$\beta_{3j} = \gamma_{3.0} + \gamma_{3.1}(\text{Experien})_j + \gamma_{3.2}(\text{Parttea})_j + \gamma_{3.1}(\text{Partici})_j + \gamma_{3.2}(\text{Schoolsize})_j + u_{3j},$$
$$\beta_{4j} = \gamma_{4.0} + \gamma_{4.1}(\text{Experien})_j + \gamma_{4.2}(\text{Opptolea})_j + \gamma_{4.1}(\text{PriAch})_j + u_{4j},$$
$$\beta_{5j} = \gamma_{5.0} + \gamma_{5.1}(\text{PriAch})_j + u_{5j},$$
$$\beta_{6j} = \gamma_{6.0} + u_{6j}.$$

Results from testing this model, model 1, are illustrated in Table 9. These results are based on 68 of 101 schools that had sufficient data for computation. The results indicated that several of the school level variables could be dropped because of low significance values ($p<0.10$). The new student level equation is illustrated as:

$$\text{Phyach}_{i,j} = \beta_{0j} + \beta_{1j}(\text{Priorach})_{i,j} + \beta_{2j}(\text{Priorsci})_{i,j} + \beta_{3j}(\text{Gender})_{i,j} + \beta_{4j}(\text{Math})_{i,j} + \beta_{5j}(\text{Opptolea})_{i,j} + \beta_{6j}(\text{Identit})_{i,j} + r_{i,j}$$

with the school level equations represented as

$$\beta_{0j} = \gamma_{0.0} + \gamma_{0.1}(\text{Science})_j + \gamma_{0.2}(\text{PriAch})_j + u_{0,j},$$
$$\beta_{1j} = \gamma_{1.0} + \gamma_{1.1}(\text{PriAch})_j + u_{1j.},$$
$$\beta_{2j} = \gamma_{2.0} + \gamma_{2.1}(\text{Identit})_j + \gamma_{2.2}(\text{Satis})_j + u_{2j.},$$
$$\beta_{3j} = \gamma_{3.0} + \gamma_{3.1}(\text{Experien})_j + u_{3j.},$$
$$\beta_{4j} = \gamma_{4.0} + \gamma_{4.1}(\text{Experien})_j + \gamma_{4.2}(\text{Opptolea})_j + \gamma_{4.1}(\text{PriAch})_j + u_{4j},,$$

$\beta_{5j}=\gamma_{5,0}+\gamma_{5,1}$ (PriAch)$_j$ + u_{5j}, ,
$\beta_{6j}=\gamma_{6,0}+u_{6j}$, .

This second model as well is based on 68 of 101 schools. The results in Table 10 show that some of the school level data are still loading at low significance levels ($p<0.10$). Consequently, a third model was tested and the results depicted in Table 11. The level 1 or student level equation in this model is represented as:

$$\text{Phyach}_{i,j} = \beta_{0j} + \beta_{1j}(\text{Priach})_{i,j} + \beta_{2j}(\text{PriSci})_{i,j} + \beta_{3j}(\text{Gender})_{i,j} + \beta_{4j}(\text{Math})_{i,j} + \beta_{5j}(\text{Opptolea})_{i,j} + \beta_{6j}(\text{Identit})_{i,j} + r_{i,j}$$

with the level 2 or school level equation represented by:

$\beta_{0j}=\gamma_{0,0}+\gamma_{0,1}$ (Science)$_j$+ $\gamma_{0,2}$ (PriAch)$_j$ + $u_{0,j}$,
$\beta_{1j}=\gamma_{1,0}+u_{1j}$,.
$\beta_{2j}=\gamma_{2,0}+\gamma_{2,1}$ (Identit)$_j$ + u_{2j}, ,
$\beta_{3j}=\gamma_{3,0}+\gamma_{3,1}$ (Experien)$_j$ +u_{3j}, ,
$\beta_{4j}=\gamma_{4,0}+\gamma_{4,1}$ (Experien)$_j$ + $\gamma_{4,2}$ (Opptolea)$_j$ + u_{4j}, ,
$\beta_{5j}=\gamma_{5,0}+u_{5j}$, .
$\beta_{6j}=\gamma_{6,0}+u_{6j}$, .

The final model, model 3, illustrates several concepts relating to student and school interactions. Class average prior achievement (**PriAch**, 0.34, p=0.00) is a significant positive determinate of the school mean achievement in physics, Intercept $\gamma_{0,0}$. In addition, whether or not the teacher teaching the physics class had a physics degree (**Science**, 0.10, p=0.00) also has a significant and positive effect on school mean achievement in physics.

Table 9

Model 1 Statistics

Student Level Predictor	School level Predictor	Coefficient	Standard Error	Significance
Intercept $\beta_{0,0}$	Intercept $\gamma_{0,0}$	-0.02	0.03	0.50
	PriAch $\gamma_{0,1}$	0.33	0.04	0.00
	Satis $\gamma_{0,2}$	0.01	0.03	0.75
	Science $\gamma_{0,3}$	0.09	0.03	0.00
Priorach $\beta_{1,0}$	Intercept $\gamma_{1,0}$	0.16	0.04	0.00
	Identit $\gamma_{1,1}$	-0.02	0.05	0.74
	PriAch $\gamma_{1,2}$	0.16	0.03	0.00
Priorsci $\beta_{2,0}$	Intercept $\gamma_{2,0}$	0.47	0.04	0.00
	Identit $\gamma_{2,1}$	0.10	0.05	0.04
	Satis $\gamma_{2,2}$	-0.06	0.03	0.04
Gender $\beta_{3,0}$	Intercept $\gamma_{3,0}$	0.07	0.02	0.00
	Experien $\gamma_{3,1}$	-0.05	0.02	0.03
	Parttea $\gamma_{3,2}$	0.01	0.02	0.74
	Partici $\gamma_{3,3}$	0.02	0.03	0.47
	SchoolSize $\gamma_{3,4}$	0.05	0.03	0.14
Math $\beta_{4,0}$	Intercept $\gamma_{4,0}$	0.22	0.03	0.00
	Experien $\gamma_{4,1}$	0.05	0.02	0.02
	Opptolea $\gamma_{4,2}$	-0.05	0.03	0.06
	PriAch $\gamma_{4,3}$	0.06	0.03	0.05
Opptolea $\beta_{5,0}$	Intercept $\gamma_{5,0}$	0.11	0.02	0.00
	PriAch $\gamma_{0,0}$	0.07	0.03	0.01
Identit $\beta_{6,0}$	Intercept $\gamma_{6,0}$	-0.06	0.02	0.00

Table 10

Model 2 Statistics

Student Level Predictor	School level Predictor	Coefficient	Standard Error	Significance
Intercept $\beta_{0,0}$	Intercept $\gamma_{0,0}$	-0.03	0.04	0.48
	PriAch $\gamma_{0,1}$	0.34	0.04	0.00
	Science $\gamma_{0,3}$	0.10	0.03	0.00
Priorach $\beta_{1,0}$	Intercept $\gamma_{1,0}$	0.23	0.05	0.00
	PriAch $\gamma_{1,2}$	0.06	0.03	0.11
Priorsci $\beta_{2,0}$	Intercept $\gamma_{2,0}$	0.48	0.05	0.00
	Identit $\gamma_{2,1}$	0.07	0.03	0.04
	Satis $\gamma_{2,2}$	-0.01	0.03	0.67
Gender $\beta_{3,0}$	Intercept $\gamma_{3,0}$	0.10	0.02	0.00
	Experien $\gamma_{3,1}$	-0.04	0.02	0.05
Math $\beta_{4,0}$	Intercept $\gamma_{4,0}$	0.18	0.03	0.00
	Experien $\gamma_{4,1}$	0.05	0.02	0.01
	Opptolea $\gamma_{4,2}$	-0.06	0.03	0.04
	PriAch $\gamma_{4,3}$	-0.03	0.03	0.36
Opptolea $\beta_{5,0}$	Intercept $\gamma_{5,0}$	0.08	0.02	0.00
	PriAch $\gamma_{0,0}$	0.03	0.03	0.30
Identit $\beta_{6,0}$	Intercept $\gamma_{6,0}$	-0.03	0.03	0.08

Table 11

Model 3 Statistics (Fixed Effects)

Student Level Predictor	School level Predictor	Coefficient	Standard Error	Significance
Intercept $\beta_{0,0}$	Intercept $\gamma_{0,0}$	-0.03	0.03	0.48
	PriAch $\gamma_{0,1}$	0.34	0.03	0.00
	Science $\gamma_{0,3}$	0.10	0.03	0.00
Priorach $\beta_{1,0}$	Intercept $\gamma_{1,0}$	0.24	0.05	0.00
Priorsci $\beta_{2,0}$	Intercept $\gamma_{2,0}$	0.48	0.05	0.00
	Identit $\gamma_{2,1}$	0.06	0.03	0.04
Gender $\beta_{3,0}$	Intercept $\gamma_{3,0}$	0.10	0.02	0.00
	Experien $\gamma_{3,1}$	-0.04	0.02	0.05
Math $\beta_{4,0}$	Intercept $\gamma_{4,0}$	0.18	0.03	0.00
	Experien $\gamma_{4,1}$	0.05	0.02	0.01
	Opptolea $\gamma_{4,2}$	-0.06	0.03	0.03
Opptolea $\beta_{5,0}$	Intercept $\gamma_{5,0}$	0.08	0.02	0.00
Identit $\beta_{6,0}$	Intercept $\gamma_{6,0}$	-0.03	0.02	0.08

Table 12

Model 3 Statistics (Random Effects)

Student Level Predictor (slope)	Variance Component	Chi-Square	Significance
Intercept $u_{0,0}$	0.10	436.82	0.00
Priorach $u_{1,0}$	0.09	136.38	0.00
Priorsci $u_{2,0}$	0.08	111.32	0.00
Gender $u_{3,0}$	0.00	76.05	0.19
Math $u_{4,0}$	0.02	102.46	0.00
Opptolea $u_{5,0}$	0.02	122.29	0.00
Identit $u_{6,0}$	0.06	69.48	0.39

The relationships of school factors with the student background predictors have mediating effects in certain circumstances. The positive impact of student prior achievement (**Priorach** , 0.24, p=0.00) is significant in predicting student achievement in physics, but is unaffected by any characteristics of the schools that are measured. This is not true of prior science achievement (**Priorsci**, 0.48, p=0.00), which is influenced positively when students in a school have higher degrees of identity (**Identit**, 0.06, p=0.04). Consequently, when schools have high ratings of identity, the influence of prior achievement in science can go as high as 0.54. Gender has a smaller effect on physics achievement (**Gender**, 0.10, p=0.00). Being male meant a student would have slightly better success with physics. This effect, however, is tempered, going as low as 0.06 when a more experienced teacher (**Experien**, -0.04, p=0.05), is teaching the course. Whether or not the student decides to do the advanced math course also has a significant impact on determining achievement levels in physics (**Math**, 0.18, p=0.00). This effect is influenced at the school level by two variables: teacher experience (**Experien**, 0.05 p=0.01) and the degree to which students in a school feel the school provides them with an opportunity to learn (**Opptolea**, 0.08, p = 0.03). Combined, these effects can push the influence of doing the advanced math course from 0.18 up to 0.27.

Student perceptions as measured by the QSL refer to the affective environment in which students find themselves. Only two of the QSL factors have impacts on physics achievement in this study. These are opportunity to learn (**Opptolea**, 0.08, p=0.00) and the extent to which students have an identity with the school (**Identit**, -0.03, p=0.08). Neither of these perceptions is influenced by the school variables measured in this study.

Apportioning the Variance

The point of the previous analysis was to reduce unexplained variance attributed to the student level (within school effects) and school level (between school effects) for the outcome variable, student achievement in physics. This is consistent with the ideas expressed by Bryk and Raudenbush (1992). A comparison of the residual variance between this model and unconditional models formulated in this section will give some information on the usefulness of the model.

Base variance within the model was calculated using an unconditional equation. This base variance refers to the total amount of unexplained variance that is attributable to student level effects and school level effects. The unconditional hierarchical model equations for achievement were:

$$\text{Phyach}_{i,j} = \beta_{0j} + r_{ij},$$

at level 1and

$$\beta_{0j} = \gamma_{00} + u_{0j}$$

at level 2.

These equations are equivalent to an analysis of variance with r_{ij} representing the within group variance and u_{0j} representing the between group variance (Bryk &Raudenbush, 1992). The results depicted in Table 12 show the variance breakdown as approximately 86.4% at the student level and 13.6% at the school level. The final model presented in the analysis illustrates that the amount of unexplained student variance and school variance has decreased to 0.27 at the student level and to 0.10 at the school level as illustrated in Table 12. The model developed in this study, then is capable of explaining a total of 64.0% of a student's grade in physics.

Table 13

Proportions of Variance Explained by the Model for both the Student and School Levels

Level	Base Variance	Model 3 Variance	Percentage decrease
Student	0.89	0.27	69.6%
School	0.14	0.10	28.6%
Total	1.03	0.37	64.0%

Predictors of the QSL

One of the questions asked in this study is whether or not the QSL factors are influenced by background student characteristics. If indeed this is true, a hierarchical model, which predicts QSL scores, will have less error if the student background variables are used as predictors in the level 1 equation. Since this portion of the analysis is speculative in nature, a full analysis, as was done in the case of physics achievement, is not required. All that is required is to consider if the background student characteristics have any influence on student perceptions. The results, when the opportunity to learn variable was treated as an outcome variable, are illustrated in Table 14 and are based on the following level 1 equation:

$$\text{Opptolea} = \beta_{0j} + \beta_{1j}(\text{Gender})_{ij} + \beta_{2j}(\text{Math})_{ij} + \beta_{3j}(\text{Priorsci})_{ij} + \beta_{4j}(\text{Priorach})_{ij} + r_{ij}\,,$$

with the level 2 equations specified as follows:

$$\begin{aligned}
\beta_{0j} &= \gamma_{0.0} + u_{0j}\,,\\
\beta_{1j} &= \gamma_{1.0} + u_{1j}\,,\\
\beta_{2j} &= \gamma_{2.0} + u_{2j}\,,\\
\beta_{3j} &= \gamma_{3.0} + u_{3j}\,,\\
\beta_{4j} &= \gamma_{4.0} + u_{4j}\,,
\end{aligned}$$

A similar level 1equation:

$$\text{Identit} = \beta_{0j} + \beta_{1j}(\text{Gender})_{ij} + \beta_{2j}(\text{Math})_{ij} + \beta_{3j}(\text{Priorsci})_{ij} + \beta_{4j}(\text{Priorach})_{ij} + r_{ij}\,,$$

with the level 2 equations being:

$$\begin{aligned}
\beta_{0j} &= \gamma_{0.0} + u_{0j}\,,\\
\beta_{1j} &= \gamma_{1.0} + u_{1j}\,,\\
\beta_{2j} &= \gamma_{2.0} + u_{2j}\,,\\
\beta_{3j} &= \gamma_{3.0} + u_{3j}\,,\\
\beta_{4j} &= \gamma_{4.0} + u_{4j}\,.
\end{aligned}$$

is used for the student's identity-with-school variable. These results too are depicted in Table 14. The results indicate that student background characteristics do have some influence on the QSL factors. Opportunity-to-learn is influenced by both gender

(**gender**, -0.07, p=0.01) and prior science achievement (**priorsci**, 0.38, p=0.00). This indicates that there is likely a causal influence within the student level data for this variable since both gender and prior science achievement also influenced physics achievement. Similarly, the student's identity-with-their-school factor is influenced by gender (**gender**, 0.21, p=0.00), again supporting a causal influence hypothesis.

An analysis of variance for both the QSL factors illustrates that most variance found within the factors is due to student level effects. For opportunity-to-learn, the proportions of variance for the student and school levels stand at 95.6% and 4.4% respectively. For the student's-identity-with-a-school the results illustrate a 93.5% versus 6.5% split between student and school. This shows that student level interests are at work within these two factors. However, the background variables in this study can explain only 16.0% and 4.0% of the variance at the student level, indicating that a more complete set of student level variables is required to sort out the intricacies of what is happening within the QSL instrument.

Table 14

Student Level Predictors of the QSL Factors

Outcome Variable	Initial Student Level Variance	Student Level Predictor	Coefficient	Significance	% of student level variance explained
Opptolea	95.6%				16.0
		Gender	-0.07	0.01	
		Priorsci	0.38	0.00	
Identit	93.5%				4.0
		Gender	0.21	0.00	

Summary

The model produced in this chapter includes variables from three data sets: student backgrounds, student perceptions and school characteristics. The original numbers of variables from these data sets were reduced by methods of factor analysis and hierarchical analysis from 35 original predictor variables to 11 predictors in the final model. Proportions of variance explained by the model are notable for both the student level and for the school level data, standing at 69.6% and 28.6% respectively. The student background set of data is observed to be the most significant predictor of physics achievement. In addition, it is suggested that causal influences may be present within the student level data.

V. Conclusion

The results of this study indicate that physics achievement can be modeled in a hierarchical manner and predicted by selected student and school variables. At the outset of this research, three questions were posed as guidelines for the study. In this chapter, these questions are re-examined in light of the results. In addition, three other points will be addressed. These are: 1) the data required to effectively compare schools, 2) distinctions between proximal and distal variables, and 3) the influence of personality differences in predicting physics achievement.

Reviewing the Questions

Question #1.

Can physics achievement be modeled as a hierarchical function of school and student based variables?

The unrestricted model, with no school or student predictors, shows that 86.4% of the variance in physics achievement can be attributed to the student level differences while 13.6% is due to differences between schools. This provides a strong indication that both student and school level variables influence achievement. Once the various nonsignificant influences are removed, the resulting model can explain 69.6% of the residual variance at the student level, 28.6% at the school level amounting to 64.0% of the total residual variance.

Question #2.

Do schools differ in the degree to which student level variables can predict physics achievement?

Most of the analysis focused on the issue of model building to predict achievement, represented as the intercept of the linear equation. However, each predictor variable also has variation (slope) that may or may not change from school to school. The p-value of the coefficients listed in the random-effects portions of the analysis of the study identify whether or not the slopes for different schools are homogeneous. A significant p-value attached to the slope coefficient indicates that the variable does not have a consistent effect across different schools. In cases where the p-value is not significant, the schools appear to be reasonably homogeneous in terms of the influence the variables have on achievement.

The current study examined student characteristics that are both homogeneous and heterogeneous. Reasonable measures of homogeneity were found in the student variables. These variables are, first, the extent to which students identify with their school (Identit) and second, gender (Gender) with significance values of 0.394 and 0.186 respectively. However, the effects of whether or not a student has taken the advanced math course (Math), opportunity to learn (Opptolea), prior achievement (priorach), and prior science achievement (priorsci) change from school to school. Interestingly, the school level variables examined in this study did little to explain these differences. This provides a fair indication that the databases used in this study are incomplete in terms of identifying the variables that do contribute to differences between schools.

Question #3.

Are students' perceptions of their quality of school life influenced by the student background characteristics?

Both gender and prior science achievement are seen to be contributing factors in the prediction of the opportunity-to-learn subscale of the QSL instrument. Gender also contributes to the prediction of the identity-with-school subscale. However, both gender and prior science achievement are significant predictors of physics achievement. Based on this preliminary finding, if the hierarchical nature of this study is abandoned in favor of a causal modeling framework, these variables may be seen to have a necessarily combined influence on the outcome variable physics achievement. This provides at least some evidence that a causal influence may be present within the student level of the hierarchy. The nature of this influence needs to be clarified by some future research.

School Comparisons

One of the major findings of this study is that traditional methods of comparing schools are inadequate. Typically, schools are compared on the basis of how high the students score on a standard exam in comparison to other schools. This score, however, is a function of the student and, as this study has shown, has very little to do with the school itself. In effect if we were to randomly assign a student from one school to any other school in this study there would be little difference in that student's mark. Using a method of comparing final outcome scores on exams, then appears to be of little value when comparing the effectiveness of schools, but acceptable for determining which school has the better academic students. This supports the arguments of Willms (1992) who claims that student inputs into a school must be considered when comparing schools.

It should be mentioned that small gains in student achievement could be seen from three school characteristics. The characteristics of teacher experience, teacher qualifications, and the overall outlook of students in a school, in terms of what the schools can provide them (opportunity-to-learn factor of the QSL) are determinants of student success. This being said, however, does not remove the fact that for the most part it was the students in a school who make one school better or worse than another.

At the student level, there are also comparison difficulties. Physics achievement is enhanced a great deal when students took the advanced math course. However, some schools did not offer this course to their students, either because of lack of funding or insufficient numbers of students who wanted to take it. This places students in one school at a disadvantage when compared to students from a similar school where advanced math was offered. It would appear imperative that any future comparisons of schools take all these items into account before statements are made that compare the effectiveness of one school to another.

The Proximal/Distal Argument

The proximal/distal variable argument has been raised in a number of studies as discussed in chapters 1 and 2. The basic idea is that variables that are close to the learning behavior (such as a student's ability) are stronger predictors of achievement than variables such as school size that is more removed from the learning behavior (Wang, Haertal & Walberg, 1993). This paper supports this argument in two ways.

First, the variance attributed to the schools is 13.6% of the total variance and the remaining 86.7% is attributable to the student. This means that for the outcome of interest, physics achievement, differences in grades are mostly due to the differences between students and to a lesser extent to differences between schools.

Second, the only school level variable that predicted achievement in a significant fashion was the average prior achievement of the students in the class (0.34) and whether or not the teacher had a physics degree (0.10). The class average, being a composite of student marks, is a measure of the class's overall ability. This obviously is a more proximal variable than others such as school size. Similarly, the qualifications of a teacher teaching the course might well be considered more proximal given that this can be expected to have an influence on the teacher and student interactions in the classroom. Of all aspects of schooling, other than the students, the teacher was probably the closest to the actual learning behavior.

Personality and Science Education

The QSL is designed to measure student perceptions of their school environment. In the study it was found that two factors of the QSL are significant predictors of achievement. One of these factors has a positive influence on achievement (the extent to which the school offers an opportunity to learn) and the second (the extent to which a student identifies with school) has a negative influence. An analysis of the items (see Table 3) which compose these factors shows that the positive predictor is associated with feelings of happiness with success, a belief by students that they could help others, and confidence. The negative predictor is associated with feelings that are more social in nature, such as the belief that they, the students, had lots of friends and that they were capable of being a good friend. The differences between these two personality traits are profound and raise concerns regarding the way achievement is determined. These concerns come from the possibility that the education system being studied may be rewarding individuals that are confident while impeding students who are concerned with social issues.

Future Research

In completing the research on this subject area, several issues have been raised that require attention. One of the most interesting of these originates from the data set itself. Since the model is not fully capable of predicting achievement or comparing schools, more appropriate databases are required. This may be of great importance for the province of Newfoundland as it enters into educational partnerships with the other Atlantic Provinces. Effective comparison of school results across provinces should take into account both school and student differences. This can only be done if the databases for the provinces all contain a common core of information that is sufficient for comparisons to be made.

In addition to the questions regarding the data within the database, questions may be raised regarding the data on the student perceptions. This study is based on a population of grade 12 physics students. One might argue that perceptions existing at this point in a student's life were not the same as those existing earlier in a student's career. Indeed, the multiple factor analyses of the QSL for different student populations' support this argument. It would be interesting to trace the pattern of evolution of the perceptions through school life for various groupings of children. This idea might be pursued by looking at the variance portion of the QSL at varying stages throughout school grades. If educators could note when negative student perceptions start to appear, it might be possible to alter curricula at that point to reverse the process.

This raises a second question regarding the effect of perceptions on student achievement at different grade levels. Given that the model is based on a population that was ready to graduate from the school system is no guarantee that the same model could describe the level of success at earlier grades. Indeed perceptions may have more or less influence on achievement as the grade level changes. This can be examined by constructing a series of hierarchical analyses to examine student characteristics at different grade levels throughout the kindergarten to level 3 system. However, based on what this research has shown, the nature of a consistent measure of achievement that encompasses all students in a school needs to be addressed so that even small schools can be adequately evaluated in terms of their performance.

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