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EVALUATION OF SCHOOL SYSTEMS USING PARTIAL LEAST SQUARES (PLS) AN APPLICATION IN THE ANALYSIS OF OPEN SYSTEMS

by

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ABSTRACT

This paper describes an application of Partial Least Squares (PLS) to the analysis of open social systems. The analysis concerns science achievement at the lower secondary level of the school system in Sweden. The data set used was collected in the study by the International Association for the Evaluation of Educational Achievement (IEA) in 1970.

As a part of the strategy leading up to this comprehensive analysis, a model of school learning was developed in order to guide the statistical model. This conceptual model is holistic; it extends from the restless neuron of the individual student to the global forces of the society as a whole.

The data set contains hundreds of variables. Altogether 191 indicators or manifest variables were selected. These represented in turn 41 underlying dimensions or latent variables. In order to render such a comprehensive model also comprehensible, a strategy of hierarchically structuring the latent variables was employed. This leads to still greater complexity but makes the model easier to handle conceptually.

The Swedish school system is described briefly. The sample and the data files are also described. Equations making up the statistical model are given and the hierarchical structure in the latent variables is discussed. Selected statistical results are presented. Special attention is given to the distinction between macro-modelling and micro-modelling and some of the possibilities

that PLS with hierarchically structured latent variables offers. Finally some thoughts are given concerning the utility of PLS as a tool for systems analysis and as a tool for general scientific development work in the social sciences.

Evaluation research must be based on theory. Theory is required at all stages of research, from sampling design, to instrument construction, to data analysis, to interpretation and reporting. Section 3 provides an overview of the theoretical model used in the present study. Section 4 describes the population and the sample investigated, the data set used, and the PLS hierarchically structured path model tested in the analysis. Section 5 reports some of the main results and discusses their implications. The main aim of Section 5, however, is not to draw substantive conclusions but to illustrate the potential of PLS for the analysis of social systems. Section 6 concludes with some observations about the use of PLS path analysis for the study of open systems.

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1. INTRODUCTION

1.1 Aims

This paper describes an application of Partial Least Squares (PLS) to the analyis of open social systems. School systems are highly complex open social systems, and no single approach to evaluation can possibly provide all the kinds of information needed for policy making. PLS is well suited to the analysis of complex open systems, however, and is superior in many applications because it does not require the user to impose hard assumptions on the model. In the present paper we restrict our view to the evaluation of the impact of school variables on the measured cognitive and affective outcomes in students. We shall try to avoid the use of technical jargon as much as possible, but it cannot be altogether eliminated.

1.2 Organization of the Paper

The present study places evaluation of school systems within a systems-analytic perspective. This puts extremely high demands on the statistical analysis methods used. Section 2 describes some of the essential requirements for the statistical methods.

Evaluation research must be based on theory. Theory is required at all stages of research, from sampling design, to instrument construction, to data analysis, to interpretation and reporting. Section 3 provides an overview of the theoretical model used in the present study. Section 4 describes the population and the sample investigated, the data set used, and the PLS hierarchically structured path model tested in the analysis. Section 5 reports some of the main results and discusses their implications. The main aim of Section 5, however, is not to draw substantive conclusions but to illustrate the potential of PLS for the analysis of social systems. Section 6 concludes with some observations about the use of PLS path analysis for the study of open systems.

2. REQUIREMENTS FOR THE STATISTICAL METHODS

2.1 Causal Modelling as Systems Analysis

The term "systems analysis" is widely used to cover a number of different approaches to the study of phenomena. Common to these approaches is a holistic view of the phenomena. Studies in the field of education falling under the heading of systems analysis have typically examined one of three areas: (1) flows of students through the various stages and types of schooling, (2) flows of resources, such as financial resources; and (3) flows of information, for example in decision making. In line with the pioneering work of Wright (1934; 1954), H. Wold (1952; 1954), Simon (1957), and Blalock (1964) and Duncan (1971), we wish to include a fourth category, namely (4) flows of causal effects through the system, such as effects on student learning outcomes.

The present paper treats school system evaluation as a kind of systems analysis which focuses on the flow of causal influences through the school system. Such analysis must of course rely heavily on statistical material derived from nonexperimental research. The size and complexity of school systems has several implications concerning (1) the relationship between the measures and the underlying phenomena, (2) the dimensionality of the school system, and (3) the multiplicity of goals of the school system and of conflict among these goals. These areas are taken up below.

2.2 Manifest Variables and Latent Variables

Many of the theoretical constructs of greatest interest in educational evaluation cannot be measured by single observations, such as questionnaire items. Constructs such as Achievement and Attitudes are examples: they are typically measured by batteries of instruments involving tens or hundreds of items. The underlying dimensions are often inferred only with the help of factor analysis. <u>These theoretical constructs are referred to as latent variables, and their measures are referred to as manifest variables</u>. In studying school learning, the school variables cannot be studied in isolation from variables describing the students and their environments. Measurement of these constructs or latent variables can only be done indirectly through multiple indicators or manifest variables. Thus statistical estimation methods for the analysis of school systems must be capable of handling manifest variables as estimators of latent variables.

2.3 Dimensionality of the School System

School systems are highly complex. To illustrate the dimensionality of the schooling experience, it may be noted that the IEA studies of national school systems and student outcomes involve thousands of distinct measures (Husén, ed., 1967; Comber & Keeves, 1973; Purves, 1973; Thorndike, 1973; Carroll, 1975; Lewis & Massad, 1975; Peaker, 1975; Walker, 1976). A structuring of these variables into conceptually homogeneous groups is a hopelessly large task unless a hierarchical taxonomic system is used. Otherwise either the number of groups becomes so large that it is impossible to obtain an overview, or else the more limited number of groups are so large and heterogeneous that they are uninterpretable. Thus statistical estimation methods for the analysis of school system evaluation data must be capable of handling large numbers of dimensions, preferably within a hierarchical conceptual framework, and must at the same time enable the exploration of the interrelationships among them.

2.4 Multiplicity of Outcomes of the School System

The school system is a matter of importance to the whole society. Many different interest groups influence educational decision making. The system itself is made up of many levels of participation -- from the top administration to the classroom, the teacher, and the student. Thus the school system has multiple goals, and there is inevitably tension and conflict between goals. For example, there are both quantitative and qualitative goals of schooling. Trade-offs are inevitable where resources are scarce, and all resources are more or less scarce. Multiplicity of goals and conflict among the goals is a common characteristic of social systems in the real world. Thus statistical estimation methods for school system evaluation must be capable of handling multiplicity of goals and conflict among the goals.

2.5 Partial Least Squares (PLS) as a Tool for the Study of Open Social Systems

Partial Least Squares (PLS) path analysis with latent variables (Wold, 1982; 1984) is a family of methods that fills well the requirements referred to above. The definitive work on PLS is given by Wold (1982), and the largest collection of studies involving PLS is given in Jöreskog and Wold (eds., 1982, Vol. 2). Educational applications are found there and in Noonan and Wold (1980; 1983;1984) and Noonan (1978;1982).

3. SCHOOL LEARNING: MODEL OF AN OPEN SOCIAL SYSTEM

3.1 Introduction

3.1.1 School Learning. To learn is to change. School learning is distinct from other kinds of learning by virtue of the central formalized role that schools play in the transmission of culture and the preparation of young people for work. It involves the learning of some particular task or set of tasks which take place within a formal instructional setting, involving a teacher, a group of students, and a formal (more or less explicit) curriculum. The archetypical example of school learning is the development of literacy and numeracy in school children.

3.1.2 Toward a General Model of School Learning. The purpose of the present model is to explain variation in school learning. We pose several requirements on our model. First, it must be general or holistic, ie., comprehensive, involving a wide range of variables, from the most proximal to the most distal in relation to school learning. Second, it must explain a wide range of empirical observations, indicating not only which variables are most relevant but also the relative strengths of the effects. Third, it must embrace a causal mechanism sufficient to explain the observed phenomena. Fourth, it must provide a parsimonious conceptual structure. The model described below is illustrated in Figure 1.

3.2 School Learning: The Orderly Combination of Structures and Processes to Achieve Learning Goals

3.2.1 A Student Centered Model. Schooling is an enormous undertaking involving coordination of massive amounts of financial and human resources in order that students may achieve selected kinds of cognitive, affective, and conate outcomes. Ultimately, however, the outcomes of this massive undertaking are crucially dependent on the student. It is not the classrooms or the schools which learn; it is the student. Thus the first essential feature of the model of school learning is that <u>the primary actor is the student</u>. Moreover, the student is not an object but a subject -- a thinking, feeling, active human being who has a will of his own.

3.2.2 <u>Student Learning Activities and the Restless Neuron</u>. In its most covert forms, learning involves mainly the neurological processing of information -- perceiving new information, remembering stored information, analyzing, synthesizing. In its most overt forms, learning involves overt practice and the gradual establishment of new behaviors. The minimal requirement for learning to occur is neurological activity. Students learn through a complex of activities referred to here as learning activities. School learning is largely an overtly active process. To be sure, sometimes learning occurs without conscious effort on the part of either the student or the teacher. School learning, however, is formalized, institutionalized, and officially sanctioned in such a way as to minimize the chance element in learning. Curricula are written so as to guide the teaching-learning process. Teaching is structured so as to guide student learning activities. The ceaseless activity of the restless neuron is to be carefully guided and directed, for without it no quality or quantity of teaching can lead to learning in the student. Thus the second essential feature of the model is that _it is student learning activities which are the creative factor in student learning._

3.2.3 _Student Characteristics._ Knowledge of student learning activities alone is not sufficient to explain variation in student outcomes. The effectiveness of a given learning activity varies among students, and this variation is a function of such characteristics of the student as prior learnings, aptitudes and ability, and affective characteristics, including motivation. The student is, to be sure, to some extent plastic and can "learn to learn". While the teaching-learning process is going on, however, the student's ability to understand instruction and his capacity to respond is restricted. Thus the third essential feature of the model is that _the outcomes of the learning activity are constrained and enabled by characteristics of the student._

3.2.4 _Significant Others in the Near Environment._ The student does not operate in isolation from his environment. At school, the teacher strives to guide the student's overt and covert learning activities by the teaching process. At home, the parents and other family members strive to guide these activities by encouraging and helping and by expressing attitudes and opinions. Outside the home and classroom, peers exert a guiding influence (positive or negative) by providing encouragement, expressing attitudes and opinions. Thus the fourth essential feature of the model is that _student characteristics and behaviors are influenced by interactions with significant others in the near environment._ Moreover, it _only_ through influencing student characteristics and behavior that others in the environment can influence student learning.

3.2.5 _Characteristics of Significant Others_. What students derive from others is largely a function of interaction process itself. It is not what people _are_ but what they _do_ which influences students. What people do is, of course, partly a function of their characteristics, such as their cognitive structures -- knowledge, understanding, beliefs, attitudes, options, etc. For example, teacher training itself does not directly influence student outcomes, but it does influence teacher does, which in turn influences student learning behavior. Similarly, parental socioeconomic status or educational level does not in itself influence student learning, but it does influence their interaction with their children. Thus the fifth essential feature of the model is that _the interaction processes in the near environment of the student is influenced by the characteristics of the actors and of the objects in the near environment_.

3.2.6 _Objects in the Near Environment_. The student interacts not only with persons but also with objects in the near environment, such as textbooks, laboratory equipment, magazines, television sets, chemistry sets and so on. Student learning behavior is both enabled and constrained by the availability and nature of the objects in the near environment. Thus the sixth essential point about the model is that <u>student behavior is influenced by interaction with objects in the environment</u>. Note that the point concerns <u>interaction</u> with the objects, not the mere <u>existance</u> of the objects. Availability of textbooks and laboratory equipment is in itself not a condition which directly promotes school learning, but the student's interaction with them.

3.2.7 <u>The Far Environment</u>. School learning takes place not only in the near environment of the student but also in a more remote or global environment. This far environment includes the society at large, the economy, the legal system, the polity, the culture, the physical environment, <u>etc</u>. In the far environment, as in the near environment, there are both people and objects. The people are all actors -- thinking, feeling, active human beings who have wills of their own. The environment both enables and constrains social behavior. Human beings also construct the environment, within the realms of the possible. The global social processes influence students, but their influence on school learning is much less direct than the influence of the interactions which take place in the near environment. Thus the seventh essential feature of the model is that <u>the far environment of school learning indirectly influences school learning, partly by influencing students directly and partly by influencing the near environment of school learning</u> -- <u>the parents, teachers, and peers.</u>

3.3 A Conceptual Framework

3.3.1 Factors. In the above description of school learning can be found many elements and relations among elements. This complexity can be greatly reduced by a hierarchical structuring of the elements. First, two categories of factors are conceived of: (1) Processes, which include learning activities and social interaction, and (2) Structures, which include the availability and nature of objects as well as characteristics of individuals, groups, or societies. Structures and Processes are the productive factors which combine to influence, both directly and indirectly, student outcomes of school learning. Second, these two categories are further divided into three levels: (1) Individual or Intra-personal, referring to the student; (2) Social or Inter-personal, referring to the near environment of school learning and the persons with whom the student has direct interaction; and (3) Societal, referring to the global environment of school learning and persons who indirectly influence the student but with whom the student has no direct interaction. At the Individual level, the student combines Structure with Process to directly produce learning outcomes. At the Social level, Structure and Process are combined to influence learning outcomes indirectly by influencing the characteristics and behaviors of the student. At the Societal level, Structure and Process are combined to influence learning outcomes both through direct influences on the student and through indirect influences through others in the near environment of school learning.

3.3.2 <u>Goals</u>. Learning behavior is neither random nor completely determined by external factors. Explanation of learning behavior requires reference to the goals of the learner. Goals are multiple and complex and can involve internal contradiction. In addition, the actors at the Individual, Social, and Societal levels combine Structures and Processes in order to attain their own goals or their own perception and understanding of the goals of others. Thus according to the model, <u>Structures and Processes are combined in order to attain Goals</u>.

3.3.3 <u>Rules</u>. The actors do not combine Structures and Processes in complete freedom. They are guided by laws, regulations, their understanding of the way things work, culture, conventions, technology, etc. These are referred to as Rules. Thus according to the model, Structures and Processes are combined in accordance with Rules in order to attain Goals.

3.4 Principles Governing Empirical Observations

The taxonomy presented above for Elements (Structures, Processes, Goals, and Rules) and Levels (Individual, Social, and Societal) provide a framework for the collection of empirical data, but there is nothing in the model yet presented to indicate the relative strengths of the influences predicted by the model. There are seven principles which enable prediction of the empirical strength of influences.

3.4.1 _The Proximity Principle_. Only student characteristics and behaviors influence learning outcomes directly. Others operate only _indirectly_ through influences on learning behavior or characteristics. It is thus appropriate to think in terms of _causal chains_, leading from more distal through more proximal variables, to student characteristics and behaviors, and finally to student learning. Through each link in the chain, however, the influences of the _causally prior_ variables are progressively weakened by the influence of the _causally subsequent_ variables. Teacher training, for example, can promote effective teaching behavior, but there are many other influences on teacher behavior. Effective teaching behavior can lead to effective learning behaviors by students, but teaching behavior is only one of many influences on student learning behavior. At each link the influence of teacher training becomes progressively modified by the influence of other factors. This may be expressed in terms of the _Proximity Principle: For each successive link in a causal chain model, the influence of a given predictor on a given predictand is progressively weakened by the influence of other variables_. In other words, in general the closer a predictor is, causally, to a predictand the greater the influence will tend to be, _ceteris paribus_; the more remote a predictor is, the less its influence will tend to be. It follows from the Proximity Principle that the effects of student characteristics and behaviors on student learning will be powerful, teacher-student interactions less powerful, teacher behavior still less powerful, teacher training still less powerful, and expenditure on teacher still less powerful.

3.4.2 <u>The Multiplicity Principle</u>. Some factors influence learning via simple causal chains while others exert influence via more complex causal chains. For example, the influence of teaching behavior operates primarily via student learning behaviors. The influence of parental behaviors, however, are much more complex and proceed via a multiplicity of paths -- through verbal ability, attitudes, help with homework, encouragement, etc. This confluence of forces on student learning behavior may be more powerful than the simpler influence of teacher behavior, even though the influence of teacher behavior on student learning behavior is more direct. This may be expressed as the <u>Multiplicity Principle: In general, the greater the number of paths by which the influence of a given cause variable operates on a given effect variable, the greater the total effect, ceteris paribus</u>. It follows from the Multiplicity Principle that the effect of the home Structure and Process variables on student outcomes are likely to be stronger than the effects of the school and classroom Structure and Process variables, unless the latter are extraordinarily effective.

3.4.3 <u>The Continuity Principle</u>. Some links in a causal chain are more powerful than others because of the continuity of the influence. For example, student attitudes are more powerfully influenced by the attitudes of parents than by the attitudes of teachers. This is because children are typically subject to the influence of their parents over much longer periods of time, more continually or permanently, and more frequently than to the influence of their teachers. Children enter the school at the age of five or six or seven, by which time the characteristic features and behaviors of the child are already well estaolished. The child attends school typically fewer than half the days of a calender year. The typical school day represents about half or less of the waking hours of the child. The child typically constitutes a major focal point in the the activities and interactions in the home. By contrast the same child at school typically claims one-twentieth or less of the attention of the teachers time. The child typically changes teachers often. In primary school the child typically changes teacher yearly. In secondary school the student typically meets a given teacher a few hours per week during a single school year. Even in broken homes the child typically lives with one parent and has contact with the other. Even other adults with whom the child has contact within the framework of the family tend to exert an influence similar to that of the parents. Thus the observed effects of parental variables actually represent the cumulative effects of frequent and continuous interactions over a long period of time, while the observed effects of teacher variables actualy represent the cumulative effects of infrequent and discontinuous contacts over relatively short periods of time.

In other words, because of the sustained and stable nature of the parental influence, the observed effects of perental variables on outcomes would tend to be higher than the observed effects of the teacher variables even if the influence of any given single isolated interaction were the same for both parents and teachers. This may be expressed as the _Continuity Principle: In general, the more frequent, continuous, permanent, and sustained the influence of a factor is on learning, the greater the effect of that factor, ceteris paribus_.

3.4.4 _The Effectivity Principle_. Some links in causal chains are stronger than others. Some parental behaviors, for example, have stronger effects on student outcomes than others because they leave stronger and more impressions. Similarly some teacher behaviors have stronger effects because they more powerfully stimulate thought, provide insights, raise interests, lead to more effective practice, etc. This may be expressed as the _Effectivity Principle: In general, the stronger the direct causal effects of the links making up the causal chain segments, the stronger is the total effect, ceteris paribus_.

3.4.5 _The Specificity-Generality Principle_. Some phenomena are relatively general, in the sense that they appear in a wide variety of contexts. They are responses to a wide range of stimuli. Others are relatively specific, in the sense that they appear in only a few contexts. They are responses to a narrow range of stimuli. For example student attitudes toward education (ie., attitudes toward school education in general) are more general than student attitudes toward science (ie., attitudes toward school education in science). Following the same reasoning, parental attitudes toward education are more general than parental attitudes toward science. According to the model, parental attitudes should influence student attitudes. The influences are varying and complex. More general phenomena tend to constitute more general stimuli and to elicit more general response in turn. More specific phenomena tend to constitute more specific stimuli and to elicit more specific responses in turn. This relationship may be expressed as the Specificity-Generality Principle: In general, more specific cause variables tend to be more strongly related to more specific effect variables, and more general cause variables tend to be more strongly related to more general effect variables.

3.4.6 The Rules Principle. The principles discussed above concern the magnitude of causal effects, where the notion of "causal effect" is understood in the same sense as the outcome of a controlled experiment. In the present section we shall discuss non-causal association. Non-causal association is one of the characteristics of open social systems, and can have a profound influence on the observed relationships in social settings. They are also among the most difficult to understand and to deal with.

Factors directly involved in schooling can usually be more or less readily manipulated by school authorities, such as the length of the school year, the availability of instructional material and equipment, class size and level and type of staffing. Three classes of manipulation are possible: (1) changing the overall level or volume of resources available; (2) changing the mix between different factors; and (3) changing the pattern of allocation of resources among schools or students.

Consider, for example, the allocation of financial resources among schools. Three cases can be identified. First, in some countries, resources are allocated in such a way that school mean expenditure per student is in practice positively correlated with the socioeconomic status of students, for example where financing is based to a high degree on local taxation and residential patterns reflect social segregation. Second, in other countries resources are allocated more equally, for example where financing is largely centralized (Noonan, 1976). Third, in some school systems school resources may be allocated in such a way that school mean expendture per student is in practice negatively correlated with the socioeconomic status of the students, for example where low achieving students receive remedial instruction. Causal effects of expenditure are not identical for all students. Thus in a school system, the observed effect of expenditure, ie., the association the researcher observed between expenditure per student and the level of student outcomes, is confounded with the way in which financial resources are allocated. In other words, the way in which school systems allocate their resources has a profound influence on the observed correlations between expenditure per student and student outcomes. Although the discussion here has concerned the effects of school financial resources, the same problem appears in all areas of research in which allocation of _treatments_ can be steered by human will. In such situations, correlation and even regression coefficients can be capricious -- they can change from sample to sample, and they can change over time as the rules of the game change. The problems discussed here can be expressed as the _Rules Principle: The relationships observed in open social systems are subject to influence by socially established rules prevailing in the system._

3.4.7 _The Measurement Error Principle_. The principles given above in Sections 3.4.1 to 3.4.5 concern the magnitudes of the causal effects, and the principle discussed in Section 3.4.6 concerns the impact of non-causal association on the observability of causal effects in non-experimental settings. The present section concerns the impact of measurement error on empirical estimates of causal effects. Complex social phenomena are difficult to measure. Multiple indicators, or manifest variables, are used in order to estimate the underlying latent variables. Although this approach improves measurement, the survey researcher is often faced nevertheless with measures containing a great deal of error. Usually very little is known about the error. In the area of educational evaluation, measures of school achievement are relatively well developed after decades of work in educational testing. Measurement of affective outcomes of schooling is more difficult, and measurement of student learning behaviors is still more difficult. Measurement of teacher, class, and school variables suffers from severe definitional problems. School measures available to researchers often originate in the routine data collected by the school administration.

In a multivariate analysis, the effects of measurement error can be exceedingly complex even for the simplest kinds of errors. In school evaluation research the measurement problem concerns primarily variables used as predictors of achievement, and above all teacher, class, and school variables. Despite the complexity, two rules of thumb can be given for aiding in the interpretation of empirical results in the face of severe measurement problems. Suppose X1 and X2 are both causes of Y, that the causal effects are of the same magnitude, and that X1 and X2 are correlate with each other. First, random error in X1 and X2 tend to attenuate the respective parameter estimates, and the greater the error, the greater the attenuating effect. Second, random error in X1 tends to reduce the value of X1 as a "control variable" and thus tends to inflate the parameter estimate for X2.

4. CASE STUDY: THE TEACHING AND LEARNING OF SCIENCE IN SWEDEN

4.1 The School System in Sweden

Compulsory schooling in Sweden is made up of 9 years of comprehensive education, beginning at age 7 and ending at age 16. It is divided into six years of primary and three years of lower secondary schooling. Compulsory schooling is followed by voluntary upper secondary schooling including a wide range of academic and vocational programs, generally ranging in duration from two to three years. The present study investigated students at the lower secondary level. At this level virtually all children attend regular public schools. At the time of the data collection (Spring 1970), the school system was highly centralized in most essential respects, including curriculum, financing, and teacher training. Compared with many other countries, Sweden is relatively homogeneous culturally and socially, and variation between schools is lower in Sweden than in most other countries.

4.2 The Data Set

The data used in the present study were collected in Sweden in 1970 as part of the Six Subject Study of the International Association for the Evaluation of Educational Achievement (IEA), carried out in twenty-two countries (Peaker, 1975; Walker, 1976). That study included science, reading comprehension, literature, English and French as foreign languages, and civics. The present study concerns science education (Comber & Keeves, 1973).

The population investigated here included all students of age 14.0 to 14.11 at the time of testing who are enrolled in regular schooling. These students were in grades 7 and 8. The sample included 2360 students, 622 teachers, and 95 schools. The response rate was approximately 95 per cent.

4.3 The Analysis

The Swedish data file from the IEA archive set M2002 was used. In this file the student data were linked to the school and teacher data. Thus analyses with the student as the unit of analysis, concerning school and teacher effects on student learning, could be carried out.

In the selection of variables for entry into the analysis, two main sources of guidance were employed. The first was the model presented in Section 3 above. This model provides a hierarchical conceptual framework in which virtually all variables in the IEA study can classified. The second source of guidance was previous studies involving the same data set (eg., see Noonan, 1978; Noonan & Wold, 1980; Noonan, 1982; Noonan & Wold, 1983). Altogether a great deal of exploratory analysis was carried out. Variables were chosen for both conceptual and empirical qualities.

In all, 191 manifest variables were finally selected for entry into the analysis. These variables were distributed over

41 basic blocks, representing basic latent variables, each block containing between 1 and 17 manifest variables. This alone represents a great reduction in complexity, but even 41 blocks is far to much to handle conceptually.

Hierarchical structuring of the blocks reduced the complexity still further. Thus although the total number of blocks was increased from 41 to 59 (including 18 blocks representing "higher order" concepts in the latent variable hierarchy), the total number of predictors of science achievement was reduced from 40 to thirteen. Table 1 shows the number of manifest variables used to measure each latent variable. Conceptually higher order variables are denoted with one or more asterisks (*, **, or ***), each additional asterisk representing a higher conceptual level. There are eight hierarchically structured latent variables, taxonomically arranged below:

1. HOME STRUCTURE
1.1 Siblings
1.2 Reading resources

2. PEER STRUCTURE
2.1 Mean Level
<u>2.1.1 Socioeconomic status</u>
<u>2.1.2 Educational Achievement</u>
<u>2.1.3 Educational Attitudes</u>
2.2 Variation in Level
<u>2.2.1 Socioeconomic Status</u>
<u>2.2.2 Educational Achievement</u>
<u>2.2.3 Educational Attitudes</u>

3. PEER BEHAVIOR
3.1 Behavioral Mean
3.2 Behaviroal Variation

4. SCHOOL STRUCTURE
4.1 School Size
4.2 Principal's Qualifications
4.3 Personnel Resources

5. TEACHER STRUCTURE
5.1 Sex
5.2 Experience
5.3 Training
5.4 Attitudes
<u>5.4.1 Teaching Criteria</u>
<u>5.4.2 Attitudes toward Practical Work</u>

6. TEACHER BEHAVIOR
6.1 Teaching Methods
6.2 Evaluation Methods
6.3 Encourages Students
6.4 Within Class Grouping

7. STUDENT STRUCTURE
7.1 Personal Characteristics
<u>7.1.1 Sex</u>
<u>7.1.2 Maturity</u>
7.2 Cognitive Characteristics
<u>7.2.1 Verbal Ability</u>
<u>7.2.2 Logical Thinking Stage</u>
7.3 Affective Characteristics
<u>7.3.1 Attitudes toward Education</u>
<u>7.3.2 Attitudes toward Science</u>

8. STUDENT BEHAVIOR
8.1 Home
<u>8.1.1 Nonscholastic</u>
8.1.1.1 Leisure activities
8.1.1.2 Leisure reading
<u>8.1.2 Scholastic</u>
8.1.2.1 Homework practices
8.1.2.2 Time on homework
8.1.2.3 Study habits
8.2 School
<u>8.2.1 Use of Textbooks</u>
<u>8.2.2 Laboratory Work</u>

Figure 2 illustrates the student behavior hierarchy. Thus ***STBEH, STUDENT BEHAVIOR represents the highest level of the hierarchy, **STBEHH, STUDENT BEHAVIOR: HOME and **STBEHS, STUDENT BEHAVIOR: SCHOOL represent intermediate levels, and *STBEHHN, STUDENT BEHAVIOR: HOME NONSCHOLASTIC and *STBEHHS, STUDENT BEHAVIOR: HOME SCHOLASTIC represent lower levels. The prediction equations for the statistical model may use all the relevant latent variables or only the highest level of a latent variable hierarchy, depending on the interest of the user. If the user is interested in a macro-model, covering the whole system, then it is imperative for the sake of interpretability to restrict the model to the highest hierarchical level. If the user is interested in a micro-model, covering some subsystem, then the model may involve some disaggregation of the latent variable hierarchies. Thus in the initial analysis for the present study, the regression equation for predicting Science Achievement contained only 13 predictors, including 8 hierarchical latent variables which represent altogether 35 basic latent variables.

4.4 Hypothetical Relations

On the basis of the model discussed in Section 3 above, fourteen causal relations were hypothesized. They were specified as predictor relations in the usual way:

HO1: TEAMETHD = F1(**PFSTR, *PEERBEH, *SCHSTR, CLASSIZE, **TEASTR)

HO2: EVLMETHD = F2(**PFSTR, *PEERBEH, *SCHSTR, CLASSIZE, **TEASTR)

H03: ENCOURAG = F3(**PFSTR, *PEERBEH, *SCHSTR, CLASSIZE, **TEASTR)

H04: GROUPING = F4(**PFSTR, *PEERBEH, *SCHSTR, CLASSIZE, **TEASTR)

H05: STUDVERB = F5(PARENSTA, *HOMESTR, PARENBEH, *STSTRPR)

H06: REASONL = F6(PARENSTA, *HOMESTR, PARENBEH, *STSTRPR)

H07: ATTEDUC = F7(PARENSTA, *HOMESTR, PARENBEH, **PRSTR, *PEERBEH, *TEABEH, *STSTRPR, *STSTRCG)

H08: ATTSCIEN = F8(PARENSTA, *HOMESTR, PARENBEH, **PRSTR, *PEERBEH, *TEABEH, *STSTRPR, *STSTRCG)

H09: LEISACTV = F9(PARENSTA, *HOMESTR, PARENBEH, **PRSTR, *PEERBEH, **STSTRPR)

H10: LEISREAD = F10(PARENSTA, *HOMESTR, PARENBEH, **PRSTR, *PEERBEH, **STSTRPR)

H11: HWKPRACT = F11(PARENSTA, *HOMESTR, PARENBEH, **PRSTR, *PEERBEH, **STSTRPR)

H12: TIMEONHW = F12(PARENSTA, *HOMESTR, PARENBEH, **PRSTR, *PEERBEH, **STSTRPR)

H13: STUDYHAB = F13(PARENSTA, *HOMESTR, PARENBEH, **PRSTR, *PEERBEH, **STSTRPR)

H14: SCIENACH = F14(PARENSTA, *HOMESTR, PARENBEH, **PRSTR, *PEERBEH, *SCHSTR, CLASSIZE, CLASTIME, CURRICLM, **TEASTR, *TEABEH, *STSTR, ***STBEH)

The hierarchical relations were expressed with a similar set of equations.

5. RESULTS

5.1 Purpose of the Present Report

The analysis described in Section 4 yields a rich variety of results. Because of space limitations, only a small portion of these results can be reported. The purpose of this report is not primarily to draw substantive conclusions but to demonstrate the use of PLS path analysis using hierarchically structured latent variables as a tool for the analysis of open social systems.

5.2 Path Coefficients; Total Effect Coefficients

The complete analysis is illustrated in Figure 3. In this report, path coefficients and total effect coefficients (sum of direct and indirect effects) are reported for selected relations. The following dependent variables are considered: (1) Verbel Ability; (2) Attitudes toward Education; (3) Attitudes toward Science; and (4) Science Achievement.

Verbal Ability, STUDVERB. The effects of factors influencing verbal ability were estimated in accordance with hypothesis H05 above. Three effect coefficients are reported in Table 2: (1) simple correlations; (2) path coefficients; and (3) total effect coefficients. In the present case only one multiple regression is involved, so their are no indirect effects, and the total effect coefficients are equal to the path coefficients. Home Structure has by far the strongest influence on Verbal Ability, followed by Parental Status. The next strongest effect is shown by Student Personal Characteristics, and the weakest effect is shown by Parental Behavior. Only 17 per cent of the variance in STUDVERB is explained, however, suggesting that the most important sources of variation are not tapped by the model.

A more variegated picture of causal influence is shown for the latent variables representing attitudes toward education and science. Hypotheses H07 and H08 reflect the greater volitility of affective characteristics, as compared with cognitive characteristics. Thus while peer characteristics and behaviors and teacher behaviors cannot be expected to have effects on such basic characteristics of the student as verbal ability, the origins of which is in the home during the early years of the child's development, these variables can be expected to influence affective characteristics.

The estimated effects of factors influencing attitudes toward education and science are shown in Table 3 and 4, respectively. It is seen that the strongest influence on both Attitudes toward Education and Attitudes toward Science are exerted by the home variables, especially Parental Behavior. We shall investigate further below the effects of Student Personal Characteristics. Peer influences are weaker for Attitudes toward Education than for Attitudes toward Science. The general impression emerging from Tables 3 and 4 is that attitudes toward both education and science are more powerfully influenced by the home than by forces outside the home, but this distinction appears to be more pronounced in the case of attitudes toward education. In general, variation in Attitude toward Science is less strongly related to the variables in the model than is Attitude toward Education, as indicated by the fact that the squared multiple correlation for ATTEDUC is 0.31, while the squared multiple correlation for ATTSCIEN is only 0.14.

The influences on Science Achievement are the subject of Hypothesis H14. The estimated effects are shown in Table 5. Of the thirteen predictors, only seven show statistically significant effects ($p < 0.05$ based on the classical distributional assumptions are applied): *HOMESTR, CLASSIZE, CLASTIME, CURRICLM, *TEABEH, **STSTR, and ***STBEH. That the two strongest effects are shown by **STSTR and ***STBEH is completely consistent with the model presented in Section 3 above. The third strongest effects is shown by *TEABEH. The remaining variables show weak and inconsistent results, which may be attributed to sampling error and measurement error. Two variables which show unexpected negative effects are Class Time and Curriculum. The fact that <u>all</u> effect coefficients for these variables are negative suggests compensatory allocation of instructional time and possibly severe measurement problems for the measurement of students' opportunity to learn the material tested. It should be noted that in Sweden, because of its tradition of a highly centralized school system, the variation in instructional time and curriculum is low by international comparison.

The overall impression given by the results is one of consistency in general with the model given in Section 3. The model predicts that <u>only</u> student characteristics and behaviors will remain as predictors of Achievement, and that all other variables will operate through these. It follows that other predictors which show independent effects are capturing some variance in student characteristics and behaviors which is not captured by the measures of the latter measures. This provides an interpretation of the effect shown by *TEABEH. There are altogether eighteen manifest variables measuring teacher behavior, summarized by *TEABEH, and sixteen measuring student classroom behavior, summarized by *STBEHS. Only two aspects of student behavior are measured by *STBEHS, namely use of textbooks and use of laboratory equipment. Nothing concerning teacher-student interaction or other learning behaviors appears. A comparison of the manifest variables making up *TEABEH and *STBEH reveals that there is very little overlap between the two sets of measures. Thus *TEABEH appears to be measuring teacher behaviors which influence some aspects of student learning behavior which are not measured by *STUBEH but which more directly influence science achievement. Since these behaviors are not measured by *STBEHS, there is inadequate statistical control on the influence of *TEABEH. Thus the indirect effect of teacher behavior appears as a direct effect.

5.3 Micro-Modelling

By hierarchically structuring the latent variables in the macroanalysis presented in the section above, it was possible to obtain a comprehensible overview of the essential causal interrelations in a large and complex system. Such an analysis does not elimimate the need for more intensive analyses focusing more sharply on specific parts of the system. Instead it aids in identifying those parts of the system (ie., those subsystems) for which more intensive analyses are of special interest.

We may identify two types of models: (1) macro- or global models, which cover systems as a whole, and (2) micro- or local models, which cover subsystems selected for more intensive investigation. Such a mocro-model is identifiable from the results seen in Tables 2 to 5. The associated micro-model is shown in Figure 4. In the micro-model, the latent variables representing student characteristics in the macro-model, **STSTR, is disaggregated into its component parts: STUDSEX, STUDMATR, *STSTRCG, ATTEDUC, and ATTSCIEN. It could be still further broken down by disaggregating *STSTRCG into its component parts, STUDVERB and REASOML. Likewise, ***STBEH and *TEABEH could be disaggregated. Complete disaggregation of all these variables simultaneously, however, would increase the total number of variables in the model from the present nine to nineteen. This would render the model exceedingly difficult to overview and interpret. A more suitable approach for the researcher interested in examining these variables in greater detail might be to first disaggregate ***STBEH but use the aggregated form of **STSTR and *TEABEH, and then disaggregate *TEABEH and use the aggregated forms of **STSTR and ***STBEH. Of course many other choices are available.

Once the model to be analysed is specified, as in in the equation in Section 4.6 above, the analysis is carried out in the usual way. The model here was simplified by removing paths with coefficients less than 0.04, (corresponding closely to the $p < 0.05$ level of significance) and re-estimating. The path coefficients are shown in Table 6 and the total effect coefficients are shown in Table 7.

Three striking features emerge from the micro-analysis, as seen in Table 6. First is the absence of a direct influence of Parental Behaviors on Science Achievement. The Parental Behavior variable was entered into this analysis as the single variable most likely to capture the largest portion of the total home influence. It shows a direct influence on student cognitive and affective characteristics and thus has a powerful <u>indirect</u> effect on achievement, as seen in Table 7. It has no direct influence on achievement, however, This is completely consistent with the model presented in Section 3.

The second striking feature in Table 6 is the absence of a direct effect of Attitudes toward Education on Science Achievement. There appears to be a stronger influence of Student Cognitive Characteristics on Attitudes toward Education than on Attitudes toward Science. The influence of Attitudes toward Science on Student Learning Behavior and Science Achievement, however, appears to be greater than the influence of Attitudes toward

Education. It may be noted that ATTSCIEN, ***STBEH, and SCIENACH are related specifically to science, whereas *STSTRCG and ATTEDUC are more general. Thus, in accordance with the Specificity-Generality Principle, the more specific stimuli are more strongly related to the more specific responses, and the more general stimuli are more strongly related to the more general responses.

The third striking feature of Table 6 is the high proportion of variance explained, with R-squared 0.64. This value may be compared with 0.57 achieved in the macro-analysis (Table 5), or 0.53 reported in earlier analyses using the same data set (Noonan & Wold, 1980), or 0.36 given for the same data set in the international report of the IEA study (Comber & Keeves, 1973). This increase from 0.57 to 0.64 is due to the disaggregation of the hierarchical latent variable **STSTR and the use of its component parts as distinct predictors in the micro-analysis. This illustrates an important principle: the use of hierarchically structured latent variables in macro-analysis renders large and complex systems sufficiently simple to enable a comprehensive overview and at the same time sufficiently structured to preserve meaningfulness. However, it does not lead to the highest possible R-squared. The use of micro-analysis with some degree of disaggregation of the hierarchical structure leads to a higher R-squared, but it cannot yield a comprehensive overview of a large and complex system. The use of macro- and micro-analysis together can be very fruitful in systems analysis. Thus macro-analysis is a first stage in the extraction of information from a data set covering a large and complex system, revealing the structure of the system as a whole. This information can then be used in a second stage, involving micro-analysis, to reveal the structure of subsystems.

5.4 Model Evaluation

Three kinds of tests are available for the evaluation of PLS models: (1) Classical estimation of standard errors; (2) Stone-Geisser test of predictive relevance; and (3) Tukey's Jackknife. These methods and their application to PLS models are discussed elsewhere (Wold, 1982; Wold, 1984; Noonan & Wold, 1983). It may be noted that model evaluation using Least Squares methods is not disturbed by measurement errors, as it is using Maximum Likelihood methods. Instead measurement errors and other inaccuracies are embedded in the inference to be evaluated.

6. CONCLUSIONS

6.1 PLS as a Tool for Systems Analysis

A rational society requires the analysis and evaluation of social systems. Such systems are typically large, complex and open. Theoretical information about the structure and process of social systems is generally scarce. PLS represents a middle way between pure data analysis and classical model building. It is Least Squares oriented and thus offers wide scope, great flexibility, and optimal accuracy in predictive relations. These features make it a superior tool for the analysis of large and complex open social systems. It is relatively easy to use and is fast on the computer. For example the computer run for the present study required only 26.4 seconds CPU-time on an IBM 370.

6.2 PLS as a General Tool for Scientific Development Work

PLS is not only a tool for systems analysis, but also a general tol for scientific development work. Three areas can be mentioned: (1) exploratory data analysis; (2) instrument development; and (3) theory development.

6.2.1 Exploratory Data Analysis. In many cases the investigator is faced with massive quantities of data and very little theoretical information. The ease of using PLS and the rapid computation enables the user to have a close dialogue with the data, exploring a variety of models, moving manifest variables from one block to another, breaking up blocks, etc. Even when the user intends to report only simple descriptive results, such as frequenc distributions and descriptive statistics for the total sample and selected groups, PLS is a valuable tol for identifying key variables and suggesting ways of examining the data.

6.2.2 Instrument Construction. In the study of large and complex social systems, instruments (eg., questionnaires) are often of questionable quality because of the lack of theoretical information. The ordering of variables into blocks and the examination of the results of the analyses provides a great deal of information about the way the instruments work. From the computer output it is possible to identify individual items or groups of items which do not function as expected. In some cases the problem can be traced to the incorrect use of a variable, _eg_., the user discovers that the variable should be placed in another block. In other cases the problem can be traced to poor instrument construction, _eg_., ambiguous phrasing of an item, inadequate conceptualization, _etc_. Such information is valuable in the construction of new instruments.

6.2.3 _Theory Development_. Because of its ease of use, scope, and flexibility, PLS enables the user to obtain an overview -- a holistic perspective -- that promotes the development of systemic models. It encourages broad and comprehensive theory, rather than narrow and restricted theory. It can be seen in Noonan and Wold (1984), for example, how the use of PLS encouraged the development of a much wider range of variables than previous models of school learning. This model, developed further in the present paper, extends the range of explanation far beyond the psychological and curricular factors to school resources and structure, home and parental factors, and societal factors.

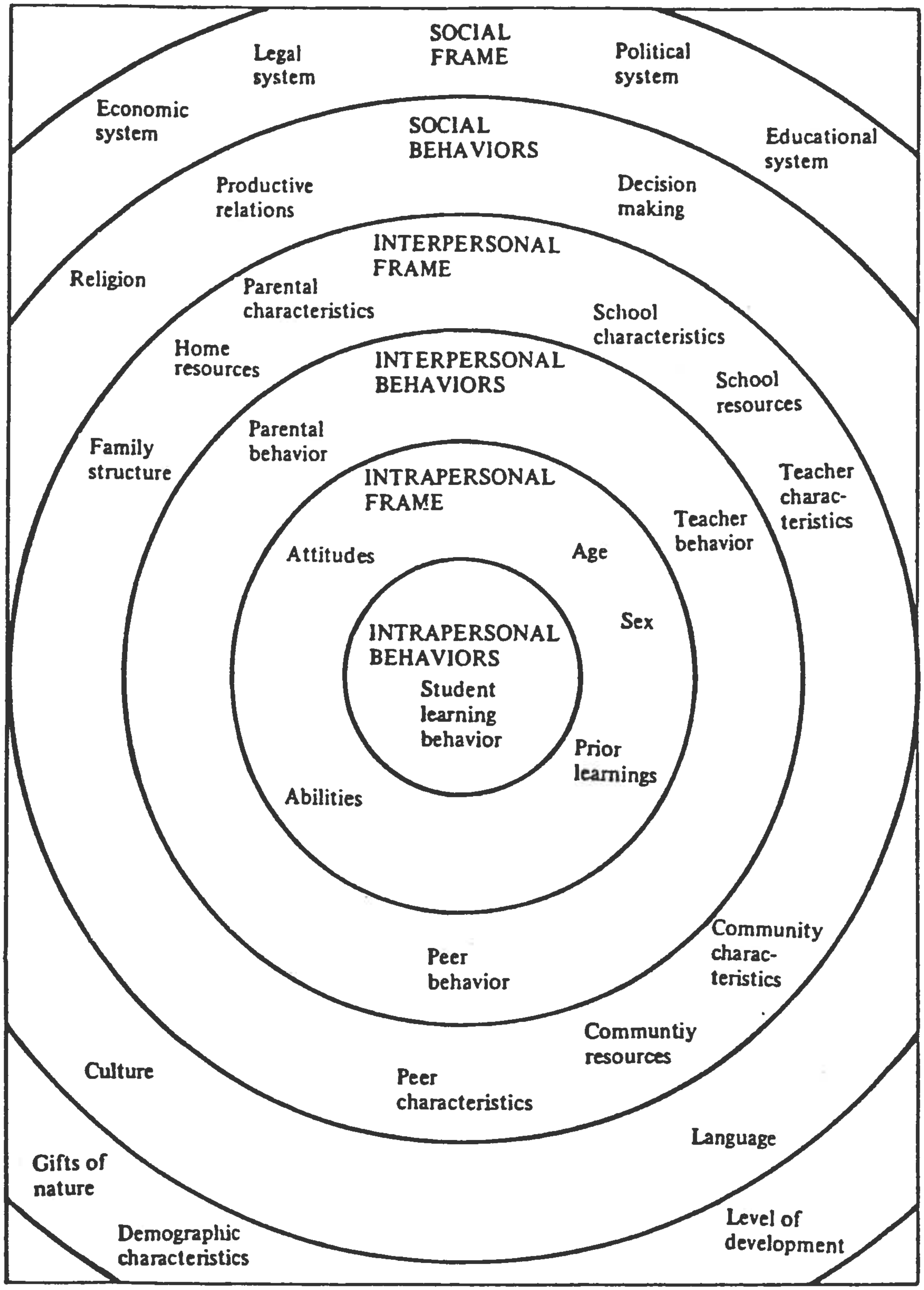
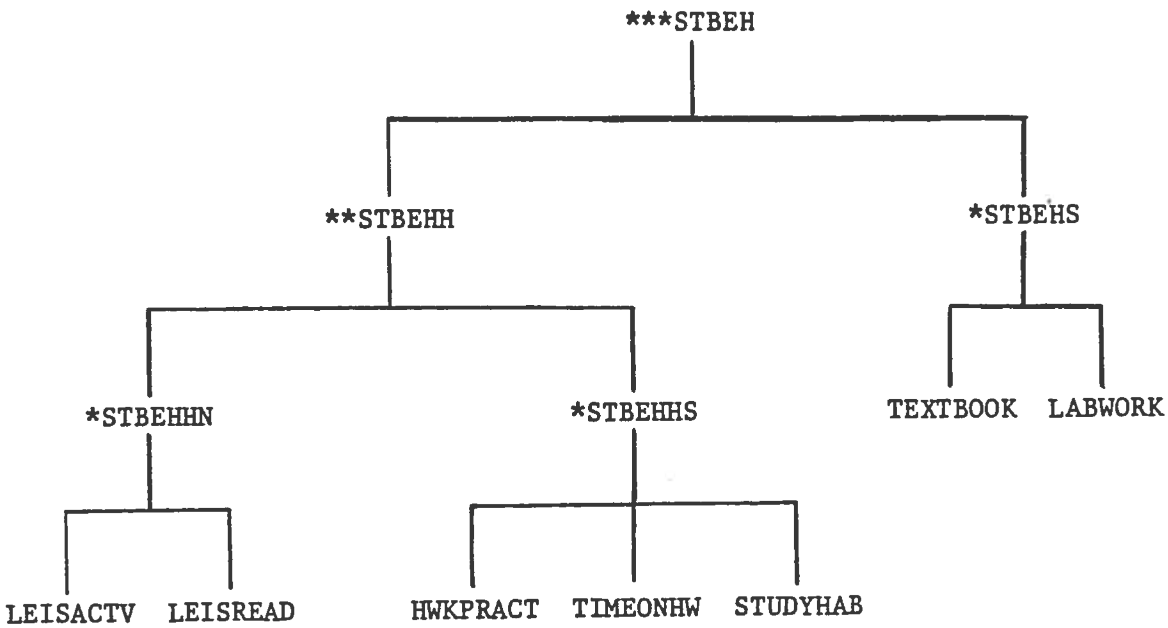


Figure 1. A General Model of School Learning



Hierarchical Latent Variables:	***STBEH	STUDENT BEHAVIOR
	**STBEHH	STUDENT BEHAVIOR:HOME
	*STBEHS	STUDENT BEHAVIOR:SCHOOL
	*STBEHN	STUDENT BEHAVIOR:HOME NONSCHOLASTIC
	*STBEHHS	STUDENT BEHAVIOR:HOME SCHOLASTIC

Figure 2. Student Behavior Latent Variable Hierarchy

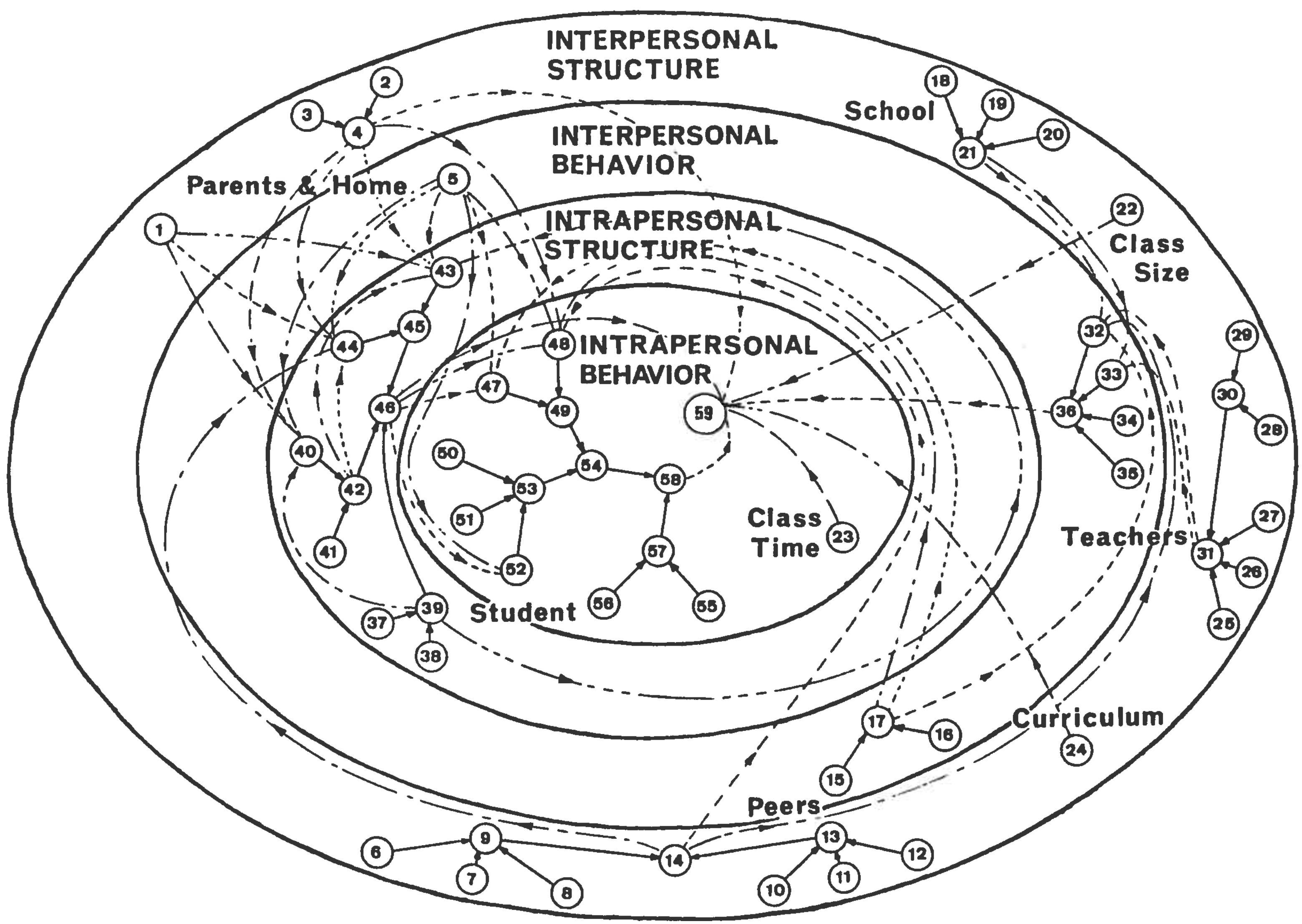


Figure 3. A General Model of School Learning: An Empirical Analysis

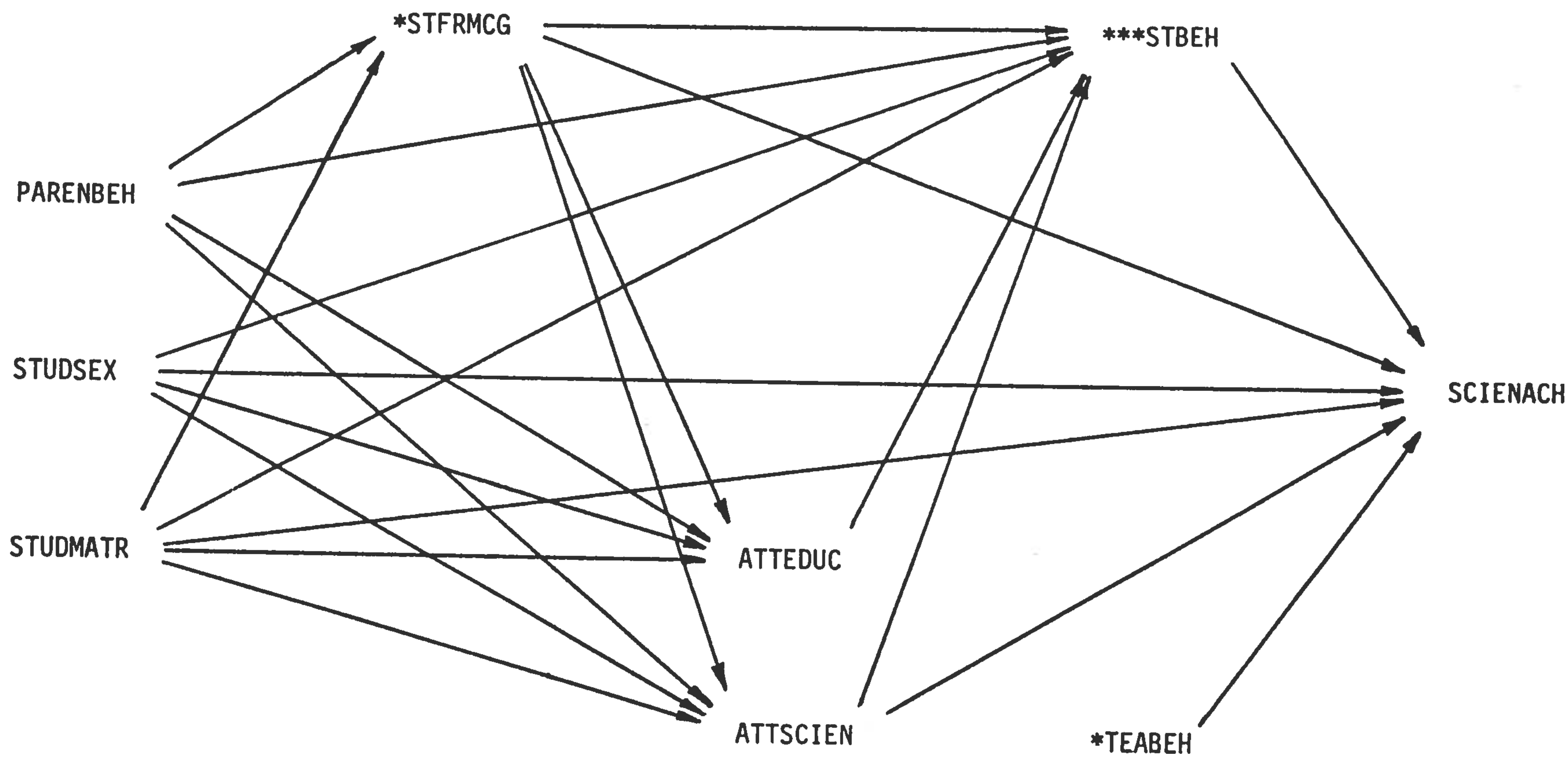


Figure 4. A Micro-Model of Influences on Science Achievement

TABLE 1. LATENT VARIABLES IN THE MODEL: NAME, LABEL, NUMBER OF MANIFEST VARIABLES

Var. No.	Name	Label	Manifest Vars.
1	PARENSTA	PARENTAL SOCIOECONOMIC STATUS	3
2	SIBLINGS	HOME SIBLINGS	3
3	HOMERESC	HOME READING RESOURCES	3
4	*HOMESTR	HOME STRUCTURE	6
5	PARENBEH	PARENTAL BEHAVIOR	7
6	PEERSTA	PEER SOCIOECONOMIC STATUS	1
7	PEERACH	PEER EDUCATIONAL ACHIEVEMENT	2
8	PEERATT	PEER EDUCATIONAL ATTITUDES	2
9	*PRSTME	PEER STRUCTURE: MEAN	5
10	PEERSESD	PEER SOCIOECONOMIC VARIATION	1
11	PEERACSD	PEER ACHIEVEMENT VARIATION	2
12	PEERATSD	PEER ATTITUDE VARIATION	2
13	*PRSTRVA	PEER STRUCTURE: VARIATION	5
14	**PRSTR	PEER STRUCTURE	10
15	PEERBEHV	PEER BEHAVIOR	3
16	PEERBESD	PEER BEHAVIORAL VARIATION	3
17	*PEERBEH	PEER BEHAVIOR	6
18	SCHLSIZE	SCHOOL SIZE	1
19	PRINCIPL	SCHOOL PRINCIPAL'S QUALIFICATION	4
20	SCHLRESC	SCHOOL PERSONNEL RESOURCES	10
21	*SCHLSTR	SCHOOL STRUCTURE	15
22	CLASSIZE	CLASS SIZE	4
23	CLASTIME	CLASS CLASS TIME	8
24	CURRICLM	CURRICULUM OPPORTUNITY TO LEARN	4
25	TEACHSEX	TEACHER SEX	1
26	TEACHEXP	TEACHER EXPERIENCE	3
27	TEATRAIN	TEACHER TRAINING	17
28	TEAATCRI	TEACHER TEACHING CRITERIA	5
29	TEAATSCI	TEACHER ATTITUDES ON PRACTICAL	10
30	*TEAATTS	TEACHER ATTITUDES	15
31	**TEASTR	TEACHER STRUCTURE	36
32	TEAMETHD	TEACHER BEHAVIOR: TEACHING METHODS	10
33	EVLMETHD	TEACHER BEHAVIOR: EVALUATION METHODS	5
34	ENCOURAG	TEACHER BEHAVIOR: ENCOURAGES STUDENTS	2
35	GROUPING	TEACHER BEHAVIOR: WITHIN CLASS GROUPING	1
36	*TEABEH	TEACHER BEHAVIOR	18
37	STUDNSEX	STUDENT SEX	1
38	STUDMATR	STUDENT MATURITY	2
39	*STUDSTR	STUDENT PERSONAL CHARACTERISTICS	3
40	STUDVERB	STUDENT VERBAL ABILITY	3
41	REASONL	STUDENT LOGICAL THINKING STAGE	1
42	*STSTRCG	STUDENT STRUCTURE: COGNITIVE	4
43	ATTEDUC	STUDENT: ATTITUDES TOWARD EDUCATION	10

(Continued)

TABLE 1. LATENT VARIABLES IN THE MODEL: NAME, LABEL, NUMBER OF MANIFEST VARIABLES (Continued)

Var. No.	Name	Label	Manifest Vars.
44	ATTSCIEN	STUDENT: ATTITUDES TOWARD SCIENCE	7
45	*STSTRAF	STUDENT STRUCTURE: AFFECTIVE	17
46	**STSTR	STUDENT STRUCTURE	24
47	LEISACTV	STUDENT BEHAVIOR: LEISURE ACTIVITIES	7
48	LEISREAD	STUDENT BEHAVIOR: LEISURE READING	5
49	*STBEHHN	STUDENT BEHAVIOR: HOME NONSCHOLASTIC	12
50	HWPRACT	STUDEMT BEHAVIOR: HOMEWORK PRACTICES	6
51	TIMEONHW	STUDENT BEHAVIOR: TIME ON HOMEWORK	5
52	STUDYHAB	STUDENT BEHAVIOR: STUDY HABITS	6
53	*STBEHHS	STUDENT BEHAVIOR: HOME SCHOLASTIC	17
54	**STBEHH	STUDENT BEHAVIOR: HOME	29
55	TEXTBOOK	STUDENT BEHAVIOR: USE OF TEXTBOOKS	4
56	LABWORK	STUDENT BEHAVIOR: LABORATORY WORK	12
57	*STBEHS	STUDENT BEHAVIOR: SCHOOL	16
58	***STBEH	STUDENT BEHAVIOR	45
59	SCIENACH	SCIENCE ACHIEVEMENT	5

TABLE 2. EFFECT COEFFICIENTS FOR FACTORS INFLUENCING STUDENT VERBAL ABILITY

Factor	Effect Coefficient Correlation	Path	Total
PARENSTA	0.277	0.195	0.195
*HOMESTR	0.339	0.282	0.282
PARENBEH	0.136	0.066	0.066
*STSTRPR	0.122	0.112	0.112

R = 0.415, R(2) = 0.172

TABLE 3. EFFECT COEFFICIENTS FOR FACTORS INFLUENCING STUDENT ATTITUDES TOWARD EDUCATION

Factor	Effect Coefficient Correlation	Path	Total
PARENSTA	0.330	0.171	0.231
*HOMESTR	0.320	0.149	0.230
PARENBEH	0.310	0.216	0.235
**PRSTR	0.156	0.036	0.026
*PEERBEH	0.137	0.050	0.055
*TEABEH	0.041	-0.026	-0.027
*STSTRPR	-0.087	-0.139	-0.103
*STSTRCG	0.409	0.293	0.293

R = 0.560, R(2) = 0.314

TABLE 4. EFFECT COEFFICIENTS FOR FACTORS INFLUENCING STUDENT ATTITUDES TOWARD SCIENCE

Factor	Effect Coefficient Correlation	Path	Total
PARENSTA	0.185	0.068	0.108
*HOMESTR	0.186	0.072	0.126
PARENBEH	0.228	0.167	0.180
**PRSTR	0.181	0.106	0.087
*PEERBEH	0.153	0.049	0.060
*TEABEH	0.024	-0.051	-0.051
*STSTRPR	0.026	-0.013	0.012
*STSTRCG	0.276	0.196	0.196

R = 0.378, R(2) = 0.143

TABLE 5. EFFECT COEFFICIENTS FOR FACTORS INFLUENCING SCIENCE ACHIEVEMENT

Factor	Effect Coefficient Correlation	Path	Total
PARENSTA	0.250	0.017	0.177
*HOMESTR	0.249	-0.045	0.157
PARENBEH	0.147	-0.031	0.086
**PRSTR	0.177	-0.021	0.017
*PEERBEH	0.089	-0.038	-0.002
*SCHSTR	0.037	-0.021	-0.023
CLASSIZE	-0.092	-0.040	-0.043
CLASTIME	-0.278	-0.059	-0.059
CURRICLM	-0.136	-0.059	-0.059
*TEASTR	0.093	-0.007	0.011
*TEABEH	0.182	0.079	0.062
**STSTR	0.715	0.571	0.664
***STBEH	0.585	0.240	0.241

R = 0.756, R(2) = 0.572

TABLE 6. PATH COEFFICIENTS FOR THE MICRO-ANALYSIS

Predictand	Predictors (1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	R(2)	e
*STSTRCG	13	.	16	.	.	.	.	.	04	98
ATTEDUC	26	05	-14	39	.	.	.	.	25	86
ATTSCIEN	20	-19	-09	27	.	.	.	.	16	92
***STBEH	04	-24	24	36	10	21	.	.	42	76
SCIENACH	.	-17	14	57	.	11	18	06	64	60

NOTES: 1. Coefficients are multiplied by 100.

2. Predictors: (1) PARENBEH
(2) STUDSEX
(3) STUDMATR
(4) *STSTRCG
(5) ATTEDUC
(6) ATTSCIEN
(7) ***STBEH
(8) *TEABEH

TABLE 7. TOTAL EFFECT COEFFICIENTS FOR THE MICRO-ANALYSIS

Predictand	Predictors (1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
*STSTRCG	13	.	16	.	.	.	.	.
ATTEDUC	31	05	-07	39	.	.	.	.
ATTSCIEN	24	-19	-05	27	.	.	.	.
***STBEH	17	-27	28	46	10	21	.	.
SCIENACH	13	-24	27	68	02	15	18	06

NOTES: 1. Coefficients are multiplied by 100.

2. Predictors: (1) PARENBEH
(2) STUDSEX
(3) STUDMATR
(4) *STSTRCG
(5) ATTEDUC
(6) ATTSCIEN
(7) ***STBEH
(8) *TEABEH

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