


1989

An analysis of a preservice teacher structural equation model under varying assumptions and measurement conditions

Dean K. Frerichs
Iowa State University

Follow this and additional works at: <https://lib.dr.iastate.edu/rtd>

 Part of the [Educational Assessment, Evaluation, and Research Commons](#), and the [Teacher Education and Professional Development Commons](#)

Recommended Citation

Frerichs, Dean K., "An analysis of a preservice teacher structural equation model under varying assumptions and measurement conditions " (1989). *Retrospective Theses and Dissertations*. 9122.
<https://lib.dr.iastate.edu/rtd/9122>

This Dissertation is brought to you for free and open access by the Iowa State University Capstones, Theses and Dissertations at Iowa State University Digital Repository. It has been accepted for inclusion in Retrospective Theses and Dissertations by an authorized administrator of Iowa State University Digital Repository. For more information, please contact digirep@iastate.edu.

INFORMATION TO USERS

The most advanced technology has been used to photograph and reproduce this manuscript from the microfilm master. UMI films the text directly from the original or copy submitted. Thus, some thesis and dissertation copies are in typewriter face, while others may be from any type of computer printer.

The quality of this reproduction is dependent upon the quality of the copy submitted. Broken or indistinct print, colored or poor quality illustrations and photographs, print bleedthrough, substandard margins, and improper alignment can adversely affect reproduction.

In the unlikely event that the author did not send UMI a complete manuscript and there are missing pages, these will be noted. Also, if unauthorized copyright material had to be removed, a note will indicate the deletion.

Oversize materials (e.g., maps, drawings, charts) are reproduced by sectioning the original, beginning at the upper left-hand corner and continuing from left to right in equal sections with small overlaps. Each original is also photographed in one exposure and is included in reduced form at the back of the book. These are also available as one exposure on a standard 35mm slide or as a 17" x 23" black and white photographic print for an additional charge.

Photographs included in the original manuscript have been reproduced xerographically in this copy. Higher quality 6" x 9" black and white photographic prints are available for any photographs or illustrations appearing in this copy for an additional charge. Contact UMI directly to order.

U·M·I

University Microfilms International
A Bell & Howell Information Company
300 North Zeeb Road, Ann Arbor, MI 48106-1346 USA
313/761-4700 800/521-0600

Order Number 9014897

**An analysis of a preservice teacher structural equation model
under varying assumptions and measurement conditions**

Frerichs, Dean K., Ph.D.

Iowa State University, 1989

U·M·I
300 N. Zeeb Rd.
Ann Arbor, MI 48106

An analysis of a preservice teacher structural equation model
under varying assumptions and measurement conditions

by

Dean K. Frerichs

A Dissertation Submitted to the
Graduate Faculty in Partial Fulfillment of the
Requirements for the Degree of
DOCTOR OF PHILOSOPHY

Department: Professional Studies in Education
Major: Education (Research and Evaluation)

Approved:

Signature was redacted for privacy.

In Charge of Major Work

Signature was redacted for privacy.

For the Major Department

Signature was redacted for privacy.

For the Graduate College

Iowa State University
Ames, Iowa

1989

TABLE OF CONTENTS

	Page
CHAPTER 1 INTRODUCTION	1
Background	1
Conceptual Model	4
Need for the Study	6
Statement of the Problem	8
Purpose of the Study	9
Objectives of the Study	9
Significance of the Study	10
Research Hypotheses	11
Basic Assumptions	11
Delimitations of the Study	12
CHAPTER 2 REVIEW OF LITERATURE	13
Causation and Causal Models	13
Regression Approach	16
LISREL Approach	21
Conceptual Model Variables	30
Job Expectations	31
Academic Ability	32
Pre-Student Teaching Preparation	33
Cooperating Teacher	34
Self-Rated Student Teaching Performance	34
Empirical Models	35
CHAPTER 3 METHODOLOGY	42
Data Source and Procedures	42
Subjects	43
Instrumentation	44
Analysis of Data	50
CHAPTER 4 RESULTS	55
Single Indicator Model with No Measurement Error (Model I)	58
Single Indicator Model with Adjustment for Measurement Error (Model II)	59
Multiple Indicator Model with No Adjustment for Measurement Error (Model III)	63
Multiple Indicator Model with Adjustment for Measurement Error (Model IV)	65
Single Variable Model with No Adjustment Value (Model V)	69

CHAPTER 5	SUMMARY/DISCUSSION AND RECOMMENDATIONS	75
	Summary/Discussion	75
	Recommendations for Future Research	81
BIBLIOGRAPHY		83
ACKNOWLEDGEMENTS		90
APPENDIX A	TEACHER EDUCATION PROGRAM SURVEY	91
APPENDIX B	SUGGESTED STEPS FOR STRUCTURAL EQUATION MODEL ANALYSIS	106

LIST OF TABLES

	Page	
Table 2.1	Parameter and variable identification	23
Table 3.1	Gender and teaching level of respondents	43
Table 3.2	Academic ability descriptive statistics	45
Table 3.3	Job expectations descriptive statistics	45
Table 3.4	Adequacy of preparation descriptive statistics	46
Table 3.5	Self-rated student teacher behavior descriptive statistics	47
Table 3.6	Standardized composite descriptive statistics for variables used in Models I and II	48
Table 3.7	Correlations for Models I and II (N = 271)	48
Table 3.8	Correlations for Models III, IV, and V (N = 271)	49
Table 4.1	Variable names and descriptions	56
Table 4.2	Means and standard deviations for Models I and II (N = 271)	57
Table 4.3	Correlations for Models I and II (N = 271)	58
Table 4.4	Model I parameter estimates assuming no measurement error (N = 271)	59
Table 4.5	Error estimates for Model II (N = 271)	60
Table 4.6	Model II parameter estimates with adjustment for measurement error (N = 271)	61
Table 4.7	Comparison of R square values for endogenous variables for Models I and II (N = 271)	62
Table 4.8	Means and standard deviations of observed variables for multiple indicator Models III, IV, and V	64
Table 4.9	F-values to determine significant paths for Model III (N = 271)	65

	Page
Table 4.10 Latent variables and indicators	66
Table 4.11 Multiple indicator correlations (N = 271)	67
Table 4.12 Model IV parameter estimates allowing for measurement error (N = 271)	68
Table 4.13 Model V parameter estimates for observed variables with no adjustment for measurement error (N = 271)	70
Table 4.14 Paths for quality of preparation structural equation as specified by five approaches	71
Table 4.15 Path coefficients for Models I, II, and IV (N = 271)	73
Table 4.16 R square values for all models	74

LIST OF FIGURES

	Page
Figure 1.1 Conceptual model of preservice teacher variables	7
Figure 2.1 Sample path diagram	18
Figure 2.2 Sample structural equation model	24
Figure 2.3 Model I: Single indicator model with no measurement error	37
Figure 2.4 Model II: Single indicator model with adjustment for measurement error	38
Figure 2.5 Model III: Multiple indicator model with no measurement error	39
Figure 2.6 Model IV: Multiple indicator model with adjustment for measurement error	40
Figure 2.7 Model V: Single variable model with no measurement error	41

CHAPTER 1

INTRODUCTION

The purposes of this study were to develop a structural equation model of preservice teacher variables and examine alternative methods of testing this model under different assumptions and measurement conditions. Analyzing causal relationships has been known by many names (causal modeling, simultaneous equation systems, linear causal analysis, path analysis, and others) but now is typically classified under the rubric of structural equation modeling. Based on the assumptions and measurement conditions for the conceptual model of this study, two methods were used to analyze the resulting operational structural equation models, multiple regression and LISREL. LISREL is an acronym taken from the function of a statistical package: the analysis of LInear Structural RELationships and implies parameter estimation of models that have structural equations (multiple regression type), measurement equations (factor analytic type), or both.

Background

Throughout time people have tried to develop causal explanations for what was happening in the world around them. This preoccupation with causal explanations may be justified for two reasons. First, people are often convinced that causal explanation represents a most fundamental understanding of the process that is being studied and that such knowledge remains invariant through time (Goldberger, 1973; Duncan,

1975). Secondly, it is far more useful and interesting to know that one variable is the cause of another variable rather than to know that these variables always appear together (Saris & Stronkhorst, 1984).

This fascination with causal explanation has led to much debate among researchers (for example Guttman, 1977; Asher, 1983; Cohen & Cohen, 1983; Pedhazur, 1982; Bollen, 1989). However, sociological methodologists such as Blalock (1961, 1963), Boudon (1965) and Duncan (1966) initiated a movement that demonstrated the value of combining the rigor of simultaneous equations and the simplicity of path analytic models. Because of this movement, path analysis became a major sociological research method by the 1970s (Blalock, 1971).

However, major concerns developed regarding multiple regression analysis of structural models. One concern was that models should be tested and estimated values obtained for the equations. Also, the paths must be specified as must the estimation of the values for coefficients. Within the regression approach, parameters are estimated separately for individual equations, making it difficult to perform an overall test of a theory posited by the model. Because of this, many models in the literature were not tested. Indeed, Saris and Stronkhorst (1984) estimate that more than 50 percent of models in the literature could be rejected if the data were reanalyzed using LISREL. One alternative to model testing suggested by Duncan (1975) and Heise (1969) was that nonsignificant path coefficients be removed from the model. This alternative suggests hypothesizing fully recursive models and computing parameter t-values. Parameters with t-values larger than 2 were

retained, while parameters with t-values less than 2 were omitted (set to zero).

A second concern addressed the way regression analysis deals with unobserved (latent) variables. In the social sciences, interest is often focused on relationships among latent variables. However, multiple regression estimation of models of this type results in parameters reflecting relationships among observed indicators of latent variables rather than relationships among the latent variables themselves.

In an attempt to overcome this concern, multiple indicators (two or more observed variables measuring an unobserved variable) were introduced as an alternative to the single indicator approach (Sullivan, 1971; Sullivan, 1974; Warren, Fear, & Klonglan, 1980). However, calculations were complex and tedious.

Lastly, concern was expressed toward the regression assumption of perfect measurement for all but the dependent variable (Long, 1981). Unfortunately, no measurement instrument in the social sciences is entirely accurate. The presence of measurement error may overstate or understate the causal impact of an explanatory variable and almost always inflates the disturbance term (cause due to unknown sources) of the dependent variable. Although there was concern with measurement error, initial progress was hampered by a lack of adequate statistical procedures.

It became apparent that a general method was needed to deal with these and other concerns. In late 1970 at the University of Wisconsin,

the Conference on Structural Equation Models was organized to investigate the commonalities of causal analytic methods. Social scientists were brought together whose primary research interests included the development and use of quantitative methods for analyzing causation in nonexperimental data (Goldberger, 1973). At this conference, Wiley (1973) discussed a general linear model that included unmeasured variables and Joreskog (1973) introduced a computer program for model estimation and testing. The general method which was to provide the means to estimate and test a large variety of linear models was finally realized by the Joreskog-Keesling-Wiley (JKW) model, widely known as the LISREL approach. Thus, a computer program for statistical data analysis has become so important in econometrics, psychometrics, and other social sciences that LISREL is now used to identify a method of data analysis as well as a statistical package (Long, 1983).

At approximately the same time, Fuller and his colleagues (Degraic & Fuller, 1972; Warren, White, & Fuller, 1974; Fuller & Hidioglou, 1978) were developing an errors-in-variables approach for parameter estimation. Plewis (1985) compares the advantages and disadvantages of each approach.

Conceptual Model

The decision to enter the teaching profession, teacher satisfaction, and teacher retention are important implications of the quality of a teacher education program (Darling-Hammond, Wise, & Pease, 1983; Ashton, Webb, & Doda, 1983; Chapman, 1984). Therefore, a

conceptual model of preservice education variables which may effect the quality of a teacher education program has been posited in Figure 1.1. The typical preservice program involves coursework preparation in teaching methods and subject matter content. The conceptual model developed for this study reflects this temporal ordering. It is assumed that the variables of job expectations and academic ability are developed prior to entrance to the preservice program. These variables are followed by a pre-student teaching variable (perceived adequacy of preparation) and two post-student teaching variables (satisfaction with cooperating teacher and self-rated student teaching performance). The overall dependent variable for the conceptual model is the perceived quality of teacher preparation program.

For preservice entrance variables, job expectation included how important it is that a job provide challenge and responsibility; extrinsic rewards (good salary, advancement, prestige, security); autonomy (opportunity to be creative, use special abilities, and be in control); and service (work with people and help and serve others). Academic ability for this study included grade point average at the time of admittance to the preparation program, high school rank, and ACT composite score.

Pre-student teaching preparation involved the areas of preparation for the planning and delivering of instruction; interpersonal relationships; assessing and dealing with learning problems; understanding and providing for individual differences; and monitoring, testing and evaluating student progress.

Post-student teaching evaluation included satisfaction with the student teaching cooperating teacher and a self-rating of performance in student teaching effectiveness and teaching skills. Additional rationale and background for this conceptual model will be presented in Chapter 2.

From this conceptual model, five empirical models were developed based on different assumptions and measurement conditions. Model I assumes a single observed variable measured without error for each latent variable in the conceptual model. Model II also assumes a single observed variable for each latent variable but makes an adjustment for measurement error. Models III and IV are multiple indicator extensions of Models I and II, respectively. Model III assumes no measurement error while Model IV is a full, multiple indicator model adjusting for measurement error. Model V utilizes the 16 indicators as unique variables making individual contributions. The variables are not used as multiple indicators as in Models III and IV, nor are they used as composite variables (Models I and II). The variables in Model V are assumed to be measured without error.

Need for the Study

Despite the impact of LISREL as an analytic method for structural equation models, LISREL is just beginning to be used in educational research (Keith, 1988; Stage, 1989). In particular, analyses of structural equation models in educational research have been restricted largely to the multiple regression approach (Elmore & Woehlke, 1988).

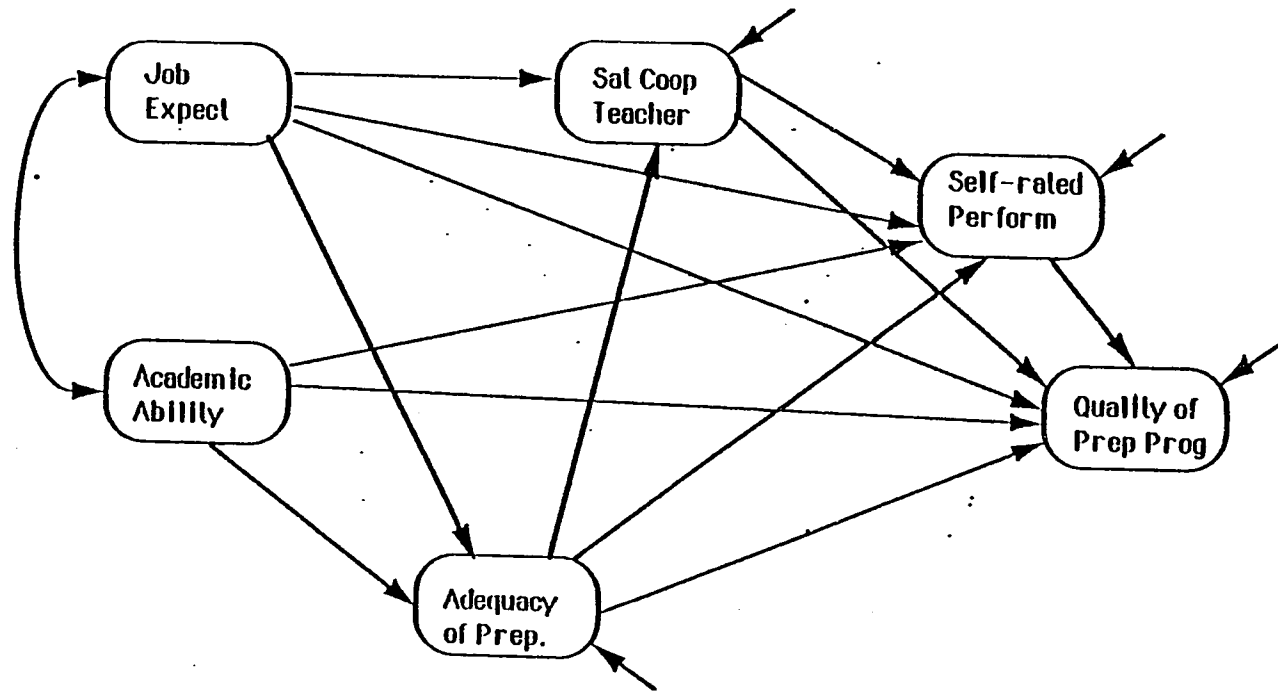


Figure 1.1. Conceptual model of preservice teacher variables

With the development of the LISREL approach, alternative analytic methods are now available to test a wide variety of structural equation models. Therefore, a need exists to demonstrate appropriate methods of analysis based on model assumptions and measurement conditions via a substantive educational research application.

Statement of the Problem

This research demonstrates methods of analyzing a structural equation model involving preservice teacher variables based on alternative assumptions and measurement conditions. Categories for alternatives to be considered include a single indicator for each unobserved (latent) variable without adjustment for measurement error, a single indicator for each latent variable with adjustment for measurement error, multiple indicators for latent variables without correction for measurement error (using the quality of preparation structural equation only), and multiple indicators corrected for measurement error.

The primary hypothesis of the model is that the quality of teacher preparation is influenced by self-rated student teaching performance, satisfaction with the student teaching cooperating teacher, perceived adequacy of preparation, importance of job expectation factors, and academic ability. A second hypothesis considered is that self-rated student teaching performance is influenced by the satisfaction with student teaching cooperating teacher, perceived adequacy of preparation, job expectation factors, and academic ability. Third, the influence of

perceived adequacy of preparation and job expectation on the satisfaction with student teaching cooperating teacher will be examined. Last, the hypothesis that academic ability and job expectation factors influence perceived adequacy of preparation will be investigated.

Purpose of the Study

The main purposes of this study were to develop a structural equation model and to examine alternative methods of analyzing a structural equation model under different assumptions and measurement conditions. A structural equation model of preservice teacher variables was analyzed with data collected from Iowa State University teacher education graduates. Based on this analysis, some general insights about structural equation modeling in educational research will be posited that may serve as a guide for other efforts in this area.

Objectives of the Study

The objectives of the study are:

1. To develop a structural equation model involving preservice teacher preparation variables.
2. To analyze a structural equation model with a single indicator for each latent variable without adjustment for measurement error.
3. To analyze a structural equation model with a single indicator for each latent variable with adjustment for measurement error.
4. To analyze a structural equation model with multiple indicators for latent variables with no correction for measurement error.

5. To analyze a structural equation model with multiple indicators for latent variables with correction for measurement error.
6. To provide an explanatory guide for selecting the appropriate method for analyzing structural equation models based on varying assumptions and measurement conditions.

Significance of the Study

The primary thrust of this dissertation is methodological; however, one should not infer that it is atheoretical. The distinction between methodology and theory has been argued by Hill (1970) as suppositious at the level of actual research and that the development of methodology is helpful to the investigation of research problems. Further, Blalock's (1968) recommendation that the extent to which the gap between theory and actual empirical research can be closed is dependent on improvement of research techniques on the one hand, and theory on the other. The examination of analytic methods for structural equation models in educational research can help adopt a workable and consistent framework for the analysis of method and theory. Furthermore, the analysis of the structural equation model involving preservice teacher education variables will provide information regarding the relationships among these variables relative to the teacher preparation program at Iowa State University.

Research Hypotheses

1. Job expectations, academic ability, adequacy of pre-student teaching preparation, satisfaction with the student teaching cooperating teacher, and self-rated student teaching performance directly affect the quality of teacher preparation.
2. Job expectations, academic ability, adequacy of pre-student teaching preparation, and satisfaction with the student teaching cooperating teacher directly affect self-rated student teaching performance.
3. Job orientation and adequacy of pre-student teaching preparation directly affect the student teaching cooperating teacher.
4. Academic ability and job expectation factors directly affect the adequacy of pre-student teaching preparation.

Basic Assumptions

The data used in this study were collected using the Teacher Education Graduate survey conducted by the Research Institute for Studies in Education (RISE) during the fall and spring semesters of 1986-87 and 1987-88. It is assumed that the survey instrument was reliable and valid in determining an accurate assessment of preservice teacher variables used in this study. It is also assumed that RISE followed proper survey procedures for the collection and coding of data.

Because measurement of variables took place at a single point in time, it is also assumed that approximations of effect over time are "arbitrarily close" (Miller, 1971, p. 289). This does not constrain the

study to assume that all effects are instantaneous.

Delimitations of the Study

The study was limited to 420 teacher education graduates that returned the Teacher Education Graduate questionnaire. The focus of this research is with graduates from the teacher preparation program. However, it is important to note that the students may be different than university students in general. To be admitted to the teacher preparation program, students must meet current admissions requirements. Usually over 90% of those admitted are juniors or seniors and must have a grade point average of 2.5 or higher and must indicate a strong interest in becoming teachers. Thus, generalizations and inferences from this analysis would be applicable to teacher preparation graduates but may not apply to all college of education graduates or university graduates in general because of the uniqueness of the teacher preparation graduates. Further, ranges of values on certain variables may be restricted for teacher preparation graduates as compared to graduates in general (for example, grade point average).

CHAPTER 2

REVIEW OF LITERATURE

This chapter has been divided into four sections. Section one addresses the notions of causality and causal models. Sections two and three present the assumptions and methods of two common approaches to structural equation analysis, linear regression (ordinary least squares) and LISREL (maximum likelihood). The last section focuses on teacher preparation variables and the development of empirical models.

Causation and Causal Models

Although the nature of causality is a topic of controversy, the analysis of causal models has become a major sociological research method (Asher, 1983; Cohen & Cohen, 1983; Pedhazur, 1982; and Bollen, 1989). This study follows Bollen's notion of probabilistic causality.

Bollen (1989), following others (for example Simon, 1954), takes a probabilistic view of causation. This view allows random disturbance representing various influences to enter the causal relationship so that a change in a causal variable is not always followed by a change in an effect variable. The random disturbance represents the effect of omitted variables, random error, or measurement error. Although a small random disturbance would imply more confidence in the causal relation, there are differences of opinion on what the size of the disturbance should be. Saris and Stronkhorst (1984) set a criterion of an R square of 0.90 or better in justifying causation. However, despite low

explained variance, causal influences may be present. In the latter case, while the causal influence may be estimated, its practical importance will be of little value (Bollen, 1989).

Bollen (1989) and others define variable X as a cause of variable Y, if a change in Y follows a change in X provided all other relevant variables are held constant. This definition implies the following three conditions (Selltitz, 1959; Kenny, 1979; Pedhazur, 1982):

- (a) X and Y covary,
- (b) a temporal ordering exists between X and Y,
- (c) the association between X and Y does not disappear when effects of causal variables prior to X and Y are removed.

Condition (a) seems to contradict the frequently quoted maxim that correlation is not proof of causation. However, it is only one of a combination of three conditions that must exist for causal interpretation. Cohen and Cohen (1983) state:

Causation manifests itself in correlation, and its analysis can only proceed through the systematic analysis of correlation ... (p. 15).

Condition (b) stipulates that the explanatory variable occurs prior to the effect variable. Temporal specification is usually straight forward since a time lag between cause and effect variables often can be determined. When a time lag is difficult to detect and order is in question, the direction of most probable influence should be specified (Rosenberg, 1968).

Condition (c) refers to nonspuriousness. To have nonspuriousness between two variables, there must not be a third variable Z that causes

both X and Y such that the relationship between X and Y vanishes when Z is removed. Put another way, X and Y are spuriously related if their covariation is mostly due to a common cause Z. This condition is not easily resolved. Typically, to investigate spuriousness between two variables X and Y, a third variable, Z, is introduced and r_{xy} is compared to $r_{xy.z}$ (Pedhazur, 1982). Unfortunately, the result of this comparison has two interpretations. First, X and Y could be spuriously related resulting in Z as a causal variable for both X and Y ($X \leftarrow Z \rightarrow Y$). The other possibility is that Z is an intervening variable resulting in X causing Z and Z causing Y ($X \rightarrow Z \rightarrow Y$).

Simon (1954) addressed the idea of what correlation proves by differentiating between true and spurious correlation. Assuming temporal ordering of variables and uncorrelated disturbances, a proof was presented supporting the claim that true correlation does imply causation in the two-variable case. The best prevention of spuriousness is careful attention to theoretical considerations.

The importance of the theoretical basis of a causal model cannot be overstated (Warren, Klonglan, & Faisal, 1977; Pedhazur, 1982; and others). Important missing variables or misspecified causal relations can generate serious bias in parameter estimation leading to erroneous conclusions. Further, it is possible that more than one model may fit the empirical data of a study equally well. The use of theory establishes model validity and helps to reveal the "causal mechanism" (Bollen, 1989; Saris & Stronkhorst, 1984) for the process under investigation.

Regression Approach

Path analysis was introduced by geneticist Sewall Wright in the 1920s. Over 40 years later, Duncan's (1966) landmark publication of sociological examples marked the beginning of path analysis as a method for social science research. By the early 1970s path analysis had become a major sociological research method (Blalock, 1971).

Using the following assumptions for path analysis (Pedhazur, 1982), the method of estimating model parameters simplifies to the solution of one or more ordinary least squares (OLS) regression analyses. The first assumption is that relationships among variables are linear and additive ruling out curvilinearly-related variables and interaction among variables. Second, residuals are not correlated with preceding variables. The implication here is that all relevant variables are included in the model and that the residuals account for random disturbances that are uncorrelated with preceding variables. Third, the causal flow is unidirectional (recursive). This eliminates reciprocal causation (two variables causing each other) between variables. It should be noted that path models with reciprocal causation (nonrecursive) can be estimated using the more complicated approach of two-stage least squares. Fourth, it is assumed that variables are measured on an interval scale. This assumption is difficult to fulfill since many social science measurement procedures lead to ordinal scales (Sarlis & Stronkhorst, 1984). Most researchers adopt Kerlinger's (1964) view of treating ordinal measurements as though they were interval

measurements but to be aware of possible inequalities of intervals. The last assumption is that independent variables are measured without error. This assumption of error-free measurement is rarely satisfied. Measurement error usually leads to underestimation of the R square value (explained variance) and may overstate or understate the estimated regression coefficients (Cochran, 1970).

The main objective of path analysis is to separate correlations into causal and noncausal parts to provide evidence of causation through an explicitly stated theory of cause and effect (Warren et al., 1977). Path analysis applications require several steps. A path diagram is constructed indicating causal relationships among relevant variables, structural equations are determined in terms of model parameters, parameters are computed using regression analyses, and results are interpreted. Each of these steps is discussed in turn.

A path diagram graphically displays the interrelationships among relevant variables and is used to provide clarity to the structure of the posited theory (Duncan, 1966). Thus, the path diagram is a graphic interpretation of the system of structural equations representing the proposed theory. Although helpful, the path diagram is not necessary for numerical computations or interpretation of results. Relevant model variables are of two types, exogenous and endogenous. Exogenous variables are assumed to have causes outside the model and endogenous variables are those with at least one hypothesized cause within the model. Causal relationships, called paths, are indicated by one-way arrows. Noncausal associations are indicated with curved two-headed

arrows. Variables not included in the model which may have causal effects on endogenous variables are called residuals or disturbances.

In Figure 2.1, X_1 and X_2 are exogenous variables and X_3 and X_4 are

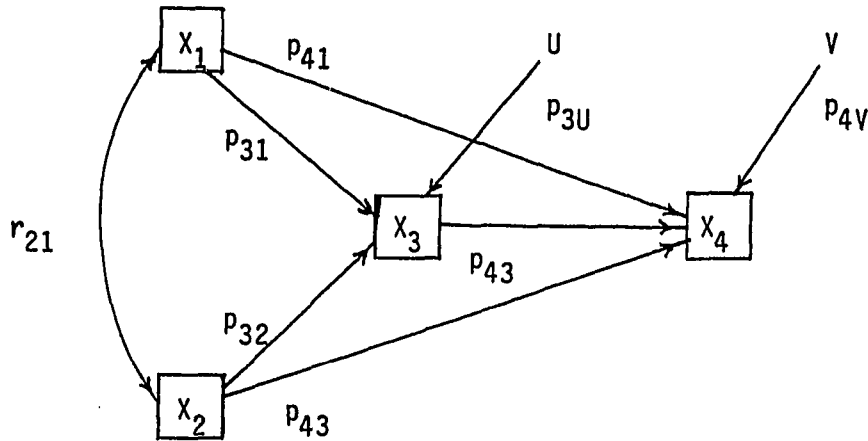


Figure 2.1. Sample path diagram

endogenous variables. The diagram indicates that X_1 and X_2 have a noncausal association; X_1 and X_2 have causal effects on X_3 and X_4 ; and X_3 causally effects X_4 . U and V represent residuals and the p_{ij} 's (i is the effect variable and j is the causal variable) represent path coefficients which link cause and effect variables (Pedhazur, 1982). Path coefficients represent the amount of effect variable change per unit change in a causal variable with all other variables held constant.

The second step is to write structural equations for endogenous variables in terms of model parameters and causal variables. Thus each endogenous variable serves as a dependent variable in an equation that

is a linear combination of causal variables and their respective path coefficients. For the model in Figure 2.1, the structural equations are

$$X_3 = p_{31} X_1 + p_{32} X_2 + e_3$$

and

$$X_4 = p_{43} X_3 + p_{41} X_1 + p_{42} X_2 + e_4$$

where e_3 and e_4 represent residuals.

The next step is to compute the model parameters. The success or failure of determining unique parameter estimates is called the identification of a model (Saris & Stronkhorst, 1984). If unique estimates for all parameters can be computed, the model is said to be identified or just identified. Just identified models can be analyzed but not tested statistically. All models satisfying the path analysis assumptions stated above will be identified. Models may also be underidentified or overidentified. Underidentified models have one or more parameters that cannot be uniquely determined so that the model cannot be analyzed. Overidentified models may have one or more parameters that may be estimated in more than one way. Overidentified models can be analyzed and tested statistically.

For the sample model in Figure 2.1, two regression analyses are required, one for each equation. For the first regression analysis, variable X_3 is regressed on X_1 and X_2 . In the second analysis, variable X_4 is regressed on X_1 , X_2 , and X_3 . The p_{ij} 's are determined by the respective beta coefficients. The R square value of each regression is the variance of the dependent variable explained by independent variables. The amount of variance of the dependent variable explained

by other sources is $1 - R$ square. Residual path coefficients are equal to the square root of $1 - R$ square.

The last step is to interpret the results. The major criterion used to evaluate the adequacy of a model is the magnitude of the coefficient of determination (R square) between the dependent variable and the independent variables of the model (Schuessler, 1971). Another method available for model evaluation is Specht's (1975) chi-square test for overidentified recursive models with uncorrelated residuals. However, the computations are somewhat complex and seldom carried out (Saris & Stronkhorst, 1984). A third method used is to remove nonsignificant paths from the model and recalculate parameter estimates for the reduced model (Heise, 1969). This has the disadvantages of post hoc application (McPherson, 1976) and not testing the model as a whole (Saris & Stronkhorst, 1984).

In addition to direct effects, total and indirect effects of variables may be of interest. The direct effect of a causal variable is transmitted directly to an effect variable and is determined by the coefficient of the path linking the two variables. Total effect is the amount of change in a dependent variable caused by a given change in an independent variable. Indirect effect of a causal variable is transmitted through one or more intervening variables to the effect variable. Fox (1980) computes direct and indirect effects using matrix calculations. Alwin and Hauser (1975) utilize systematic application of regression analyses and simple arithmetic to compute effects (Frerichs, Kemis, & Crawford, 1989). Sobel (1987) has developed a computer program

for a significance test of indirect effects.

LISREL Approach

LISREL is an approach to structural equation modeling based on the Joreskog-Keeling-Wiley (JKW) model and takes its name from the computer program used to estimate model parameters (Long, 1983). The general JKW model is a combination of a structural equation component and a measurement component which analyzes covariance structures. LISREL is capable of analyzing a wide variety of models and subsumes the regression approach as described above (Sarlis & Stronkhorst, 1984).

The underlying objective of the LISREL approach focuses on the estimation of relationships among latent (unobserved) constructs of a hypothesized model rather than relationships among observed variables (Ecob & Cuttance, 1987), a major departure from the regression approach to causal model analysis. Observed variables are specified as indicators of latent variables in the measurement model while relationships among latent variables are specified in the structural model.

Measurement and structural equation parameters indicate hypothesized relationships among model variables. Four matrices, Beta, Gamma, Lambda-X, and Lambda-Y, are used to specify causation and measurement within the causal model. Four other matrices are used to specify noncausal association among variables: Psi, Phi, Theta-delta, and Theta-epsilon. Model parameters can be specified as either fixed, free, or constrained. Fixed parameters are set equal to values

determined a priori and are supplied as input. Parameters that are to be estimated are designated as free. Constrained parameters are set equal to a single estimated value (Joreskog, 1982). Constraining plays an important part in advanced modeling techniques and should be approached with caution (Hayduk, 1987).

The LISREL notation representing parameters in a causal model is described in Table 2.1. The model in Figure 2.2 is the LISREL approach and notation applied to the model from Figure 2.1. Circles indicate latent (unobserved) variables and squares indicate observed (measured) variables. Two-headed curved arrows and one-headed arrows retain their implication of noncausal association and causality, respectively.

Using LISREL notation, the matrix structural equation component for the model in Figure 2.2 is

$$\begin{bmatrix} \eta_1 \\ \eta_2 \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ \beta_{21} & 0 \end{bmatrix} \begin{bmatrix} \eta_1 \\ \eta_2 \end{bmatrix} + \begin{bmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \end{bmatrix} \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \end{bmatrix} + \begin{bmatrix} \zeta_1 \\ \zeta_2 \end{bmatrix}$$

producing the structural equations

$$\begin{aligned} \text{and } \eta_1 &= \gamma_{11} \epsilon_1 + \gamma_{12} \epsilon_2 + \zeta_1 \\ \eta_2 &= \beta_{21} \eta_1 + \gamma_{21} \epsilon_1 + \gamma_{22} \epsilon_2 + \zeta_2 . \end{aligned}$$

The matrix form for the measurement component is

$$\begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} \lambda_{11} & 0 \\ 0 & \lambda_{22} \end{bmatrix} \begin{bmatrix} \eta_1 \\ \eta_2 \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \end{bmatrix}$$

and

Table 2.1. Parameter and variable identification

Structural equation component: $\eta = \beta\eta + \Gamma\xi + \zeta$.

Symbol	Name	Dimension	Definition
η	eta	m by 1	vector of endogenous latent variables
ξ	xi	n by 1	vector of exogenous latent variables
β	beta	m by m	coefficient matrix for latent endogenous variables
Γ	gamma	m by n	coefficient matrix for latent exogenous variables
ζ	zeta	m by 1	vector of endogenous residuals

Measurement component: $Y = \lambda_y \eta + \epsilon$ and $X = \lambda_x \xi + \delta$.

Symbol	Name	Dimension	Definition
Y	-	p by 1	observed indicators of
X	-	q by 1	observed indicators of
ϵ	epsilon	p by 1	measurement error for y
δ	delta	q by 1	measurement error for x
λ_y	lambda y	p by m	matrix of coefficients relating y to η
λ_x	lambda x	q by n	matrix of coefficients relating x to ξ
ψ	psi	m by m	covariance matrix of ζ
ϕ	phi	n by n	covariance matrix of ξ

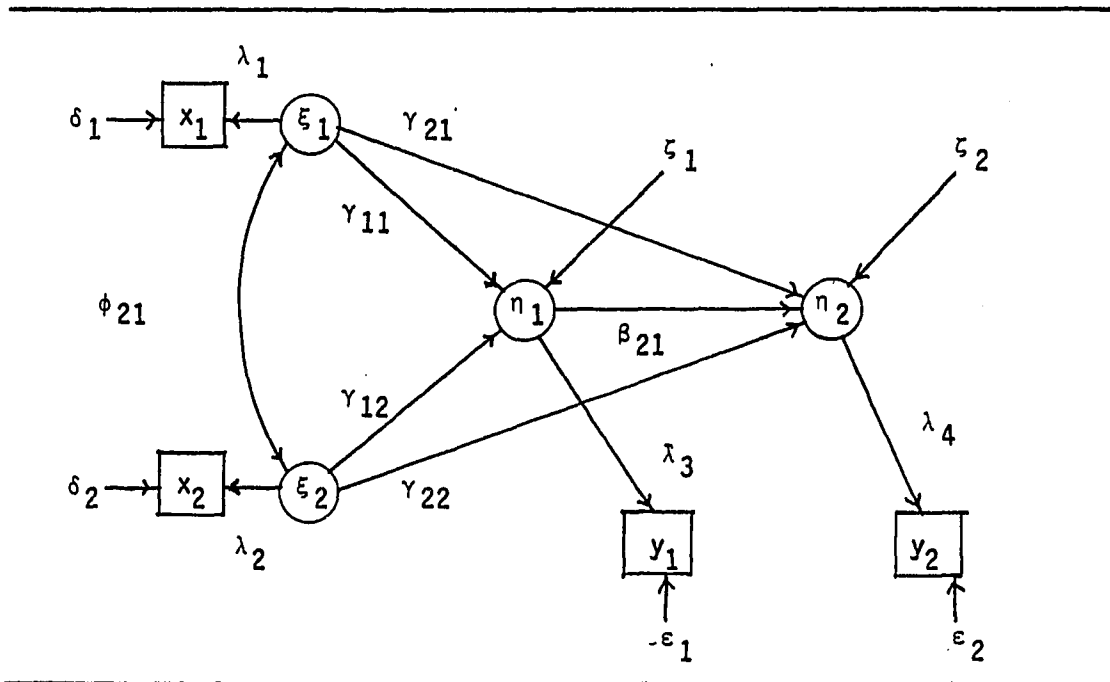


Figure 2.2. Sample structural equation model

$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} \lambda_{11} & 0 \\ 0 & \lambda_{22} \end{bmatrix} \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \end{bmatrix} + \begin{bmatrix} \delta_1 \\ \delta_2 \end{bmatrix}$$

The assumptions for LISREL have been specified by (Ecob & Cuttance, 1987). The first two assumptions are that relationships among variables are linear and additive and are measured on an interval scale. Assumption three is that disturbances in all equations have mean equal to zero. This is a necessary, but not sufficient, condition for unbiased estimates of model parameters. Fourth, disturbances are not correlated to exogenous variables. This assumption addresses model specification and implies all relevant variables are included in the

model. The fifth assumption is that errors of measurement for observed variables are not correlated with constructs. The implication is that error terms in the measurement model reflect true measurement error. Sixth, measurement errors and disturbances are mutually uncorrelated. This assumption serves mainly as a way to identify parameters of the model and is generally satisfied in most data. The last assumption is that the joint distribution of observed variables is multivariate normal. This is required for the maximum likelihood (ML) method of parameter estimation, assessment of the model fit, and tests of hypotheses about parameters. If the multivariate normal assumption cannot be met, alternative procedures of unweighted least squares and generalized least squares are available within LISREL (Saris & Stronkhorst, 1984).

Once a model has been developed, the problem of model identification should be addressed. Although no general conditions have been specified that guarantee model identification (Hayduk, 1987), Bollen (1989) has summarized conditions that are available to help determine identifiability.

One condition for identification is the t-rule. A necessary but not sufficient condition is that relationship

$$t \leq (1/2)(p + q)(p + q + 1)$$

must hold, where t is the number of parameters to be identified, p is the number of endogenous variables, and q is the number of exogenous variables. Although the t-rule is easily applied, it does not guarantee identification. A second identification condition is the null B rule, a

sufficient condition. Any model with a zero beta matrix will be identified. A beta matrix will be zero if no endogenous variable effects any other endogenous variable. Models that do not satisfy the null B rule may still be identified. The recursive rule is a third condition. Here, the beta matrix is a lower diagonal matrix and the psi matrix is diagonal. The recursive rule is sufficient for identification.

Bollen also describes more general rank and order conditions for identification of model equations. If all model equations are identified then the model is identified. If one equation is not identified then the model is not identified. Both the rank and order conditions utilize a matrix, C,

$$C = [(I - \beta) \Gamma]$$

and other matrices, g_i 's, generated from the C matrix, containing 1's for each parameter restriction and 0's otherwise. The i th equation is identified if

$$\text{order } (g_i) \geq p - 1$$

and

$$\text{rank } (Cg_i) = p - 1$$

where p = the number of endogenous variables. The order condition is necessary but not sufficient while the rank condition is a necessary and sufficient condition.

A last method of identification is Wold's rank rule. This rule involves the determination of covariances in terms of model parameters and the rank of a matrix of partial derivatives with respect to each

parameter to be estimated. Wold's rank rule is a necessary and sufficient condition for identification.

With these a priori approaches, the investigator uses either algebraic manipulation of covariances and parameters or the application of rank and order conditions. Depending on the model specified these methods can be tedious, difficult, and error-prone (Bollen, 1989). A second approach to the identification problem is post hoc examination of computer output (Joreskog, 1982). Hayduk (1987) indicates a growing trend toward the analysis of computer output to determine the identification of a model because of the difficulty of the a priori methods as applied to realistic models (e.g., the model analyzed in this study would require a 40 by 40 matrix of partial derivatives for the Wold rank rule).

Once the identification problem has been addressed, the LISREL program (Joreskog and Sorbom, 1986) can be used to generate parameter estimates and statistical tests. Input data for LISREL include sample size; number of exogenous and endogenous variables; the number of indicators for exogenous latent variables; and the number of indicators for endogenous latent variables. Data to be analyzed are entered either as correlations or variances/covariances of observed variables. Also included as input is the specification of which parameters are free, fixed, or constrained. Estimates are typically determined by the method of maximum likelihood (Joreskog, 1982).

Although many output options exist for LISREL, only three are discussed here. The first is parameter estimates. If variances/

covariances were entered as input, then default estimated parameters are output as unstandardized values (standardized estimates are available in this case). If correlations were entered as input, standardized parameter values are the default output. Second, LISREL outputs model goodness of fit information. One is a likelihood ratio chi-square value, its associated degrees of freedom, and probability value to evaluate model goodness of fit (Joreskog, 1982). A large chi-square value indicates the hypothesized model does not closely approximate the causal relationships that generated the data. Therefore, a small chi-square value is desired to indicate a good fitting model. However, an insignificant chi-square does not prove that the correct model has been found. It does indicate that one plausible model, of perhaps many, has been found which is consistent with observed covariances. Last, LISREL outputs T-values that provide a significance test for estimated parameters. A LISREL T-value is formed by dividing the parameter estimate by its standard error. A large value indicates the parameter is important to the model while a small value means the parameter is probably unimportant. The T-values have an approximate z distribution (Bentler, 1982) so that large and small can be determined by the standard normal curve.

The ease of testing the goodness of fit of a model is an important difference between the regression approach and LISREL. However, the likelihood ratio chi-square test for goodness of fit has received considerable attention, with much of the controversy focusing on sample size. Assessing goodness of fit by maximum likelihood procedures

assumes a relatively large N, yet Bentler and Bonett (1980) and others have indicated that the chi-square goodness of fit with large sample size may easily lead to the rejection of a useful theoretical model. Boomsma (1982) reports that a sample size less than 100 may lead to improper solutions. Hayduk (1987) suggests using chi-square for N in the 50 to 500 range, paying close attention to samples with modest N.

Because of this controversy, LISREL VI outputs three other goodness of fit indices. They are the Goodness of Fit Index (GFI), Adjusted Goodness of Fit Index (AGFI) and the Root Mean squared Residual (RMR). The RMR is based on the sum of squared residuals and should be close to zero for a good fit. It is not clear how large this value has to be to indicate a poor fit. The GFI is a value involving normalized measures to reduce the ambiguity of interpretation of the RMR. The GFI can have values between zero and one with, values close to one indicating a good fit and values close to zero indicating a poor fit. The AGFI is a measure of fit that adjusts the GFI using degrees of freedom. This measure also lies between zero and one, with one indicating a good fit and zero indicating a poor fit. As with the RMR, there is no standard to determine when a fit is good or poor. Saris and Stronkhorst (1984) presents a comparison of the fit indices for different models and concludes that it is "quite difficult to give simple rules for the interpretation of these indices (p 230)."

A different approach has been taken by Hoelter (1983). Hoelter has focused on sample size and proposed a formula to compute a value called Critical N (CN), which is the size of the sample that would be required

for significant results at a specified level of significance (.05 for example). Hoelter examined numerous studies and concluded that a CN of 200 or more is reasonable for an indication of a good fit.

Conceptual Model Variables

This section discusses the variables used in the empirical structural equation models. It has been hypothesized that job expectations, academic ability, perceived adequacy of preparation, satisfaction with cooperating teacher, and self-rated teaching performance have causal effects on the quality of teacher education.

The decision to enter the teaching profession, teacher satisfaction, and teacher retention are important implications of the quality of a teacher education program (Darling-Hammond, Wise, & Pease, 1983; Ashton, Webb, & Doda, 1983; Page, Page, Million, 1983) and that the preparation program may have long-term effects (Schallock, 1983).

Preparation is when an individual develops knowledge, skills and attitudes necessary to enter a chosen profession (Isaacson, 1978). In education, preservice teachers form a group of adult learners who seek formal preparation leading to recommended teaching credentials for entry into the teaching profession. It is no surprise then that the teacher preparation program plays an important role in career decisions of graduates relative to entering and remaining in the field of teaching.

Hays (1982) and Williams (1985) found that the more satisfied graduates were with their preparation, the more likely they were to enter teaching. Chapman (1984) found that preservice preparation plays

a significant role in education graduates' decisions to enter and remain in teaching. Ashton, Webb, and Doda (1983) have concluded that preparation and the efficacy derived from it influence career plans. Also, with job satisfaction playing an important role in teacher retention, inadequate preparation was found to influence dissatisfaction of teachers with their jobs (Murphy, 1982; Adams & Martray, 1980).

Job Expectations

Yarger, Howey, and Joyce (1977) focused on generalizations obtained from a national survey of preservice education. The overwhelming reason why teaching was chosen as a career was a desire to work with children. Other reasons included feelings of security, fulfillment, feelings of importance, and being challenged. Teaching was not seen as a profession that offered the opportunity for high incomes, high levels of power or status nor were these characteristics particularly important to them. Book and Freeman (1986) examined entry-level elementary and secondary education majors at a large midwestern university. Relative to career decisions, both elementary and secondary candidates were most likely to select items with a service orientation.

Chapman and Lowther (1982) proposed a conceptual scheme for describing the influences affecting teachers' career satisfaction following the work of Chapman and Hutcheson (1981). The model indicates job challenge (leadership and learning new things) and rewards (salary, recognition and approval by others) affect career satisfaction. Research by Chapman and Hutcheson (1981) investigated teacher attrition

and found that those who did and did not leave teaching differed significantly in their self-rated skills and abilities and professional success. Salary and job autonomy were the most important determinants for those who left teaching.

Williams (1985) examined the relationship of teacher preparation variables and student teaching satisfaction for Iowa State University teacher education graduates. Among others, Williams found that autonomy and job security were effective predictors of student teaching satisfaction.

Academic Ability

Academic abilities of students entering teacher preparation programs have been the focus of many studies. Research has supported the view that many who seek to enter the teaching profession are academically weak. Kerr (1983) concluded that the brightest and best are not entering teaching, Vance and Schlechty (1982) indicated that those with low measured academic ability are attracted to and remain in teaching, and Weaver (1979) concluded that a majority of new teacher graduates were in the lower half of their college class. Also, academic ability/achievement was one of several potential predictors of teaching effectiveness as suggested by Schalock (1983). Williams (1985) found that grade point at the time of admission to the teacher education program was an effective predictor of student teaching satisfaction.

No single standard has been established for entrance to teacher preparation programs. However, grade point average as a measure of

academic ability to screen preservice teacher applicants appears to be a common denominator among many institutions. Indeed, a general call for raising the standards of teacher preparation programs by the American Association of Colleges for Teacher Education (AACTE) has led to raising the grade point average entrance requirement at many institutions (Sikula and Roth, 1984).

Pre-Student Teaching Preparation

Potential predictors of teaching effectiveness as suggested by Schalock (1983) include knowledge related to teaching (including content) and skills related to teaching. In particular, Schalock lists variables being considered by Oregon Teacher Preparation Institutions as essential in research on teacher selection and preparation. Many of these characteristics can be categorized into four groups: planning and delivering instruction, interpersonal relationships, dealing with learning problems, and testing/evaluating students.

Guyton and Farokhi (1987) examined whether successful academic performance assures good teaching. Academic performance variables of teacher education graduates at one large university were correlated with on-the-job performance assessments. Many of the competencies measured can be classified in one of the four groups mentioned above. Further, Porter and Brophy (1988) summarized research on good teaching and presented a picture of effective teachers as semi-autonomous professionals who exhibit skills which also fit into the four groups mentioned previously.

Cooperating Teacher

Mandated by certification requirements, student teaching provides the opportunity for preservice teachers to observe and apply their knowledge and skills in a supervised setting. The cooperating teacher supervising and guiding a student teacher can significantly influence a student teacher during a field experience. Campbell and Williamson (1973) found that the relationship between the cooperating teacher and student teacher presented the most difficulty and stress of the field experience. Appleberry (1976) found that some student teachers felt they were given too much responsibility.

Self-Rated Student Teaching Performance

Page, Page, and Million (1983) found variables related to self-assessment of performance which combined with others to predict teacher retention. These variables include selecting and using proper questioning techniques, evaluating teaching effectiveness and making curricular revisions when necessary, using instructional time efficiently, working with large groups, working with individuals and small groups, communicating enthusiasm for learning, understanding and using appropriate subject matter, understanding the roles of other educational personnel, working with parents in the teaching/learning process, and assisting learners in developing a positive self-concept.

Heffley (1983) studied Kansas teachers leaving the profession and found that those defecting indicated more classroom problems than did

teachers remaining in teaching. This is supported by Veeman's (1984) review of 83 studies examining problems of beginning teachers. Veeman reported that the more problems that beginning teachers experienced, the more likely they were to leave teaching. Veeman identified frequent problems of beginning teachers to be classroom discipline, motivating students, dealing with individual differences, assessing students' work, relations with parents, organization of class work, insufficient materials and supplies, dealing with problems of individual students, heavy teaching load, and relations with colleagues.

In summary, individuals enter teacher preparation programs to develop the knowledge, skills, and attitudes to obtain proper credentials to enter the teaching profession. The quality of teacher education programs has been found to influence the decision of teacher education graduates to enter and remain in teaching. The framework of this investigation offers a method to study the relationships and effects among preservice variables and program quality.

Empirical Models

Therefore, based on the preceding discussion and rationale, five empirical models were developed (Figures 2.3 - 2.7). Model I (Figure 2.3) involves a single observed variable for each latent variable in the conceptual model. It is assumed that each observed variable is measured without error. Model II (Figure 2.4) also has a single observed indicator for each latent variable, however, an adjustment is made for measurement error in the observed variables. Model III (Figure 2.5) and

Model IV (Figure 2.6) are multiple indicator extensions of Models I and II. Model III assumes no measurement error while Model IV adjusts for measurement error. Finally, Model V (Figure 2.7) is a single indicator model that utilizes the 16 indicators independently.

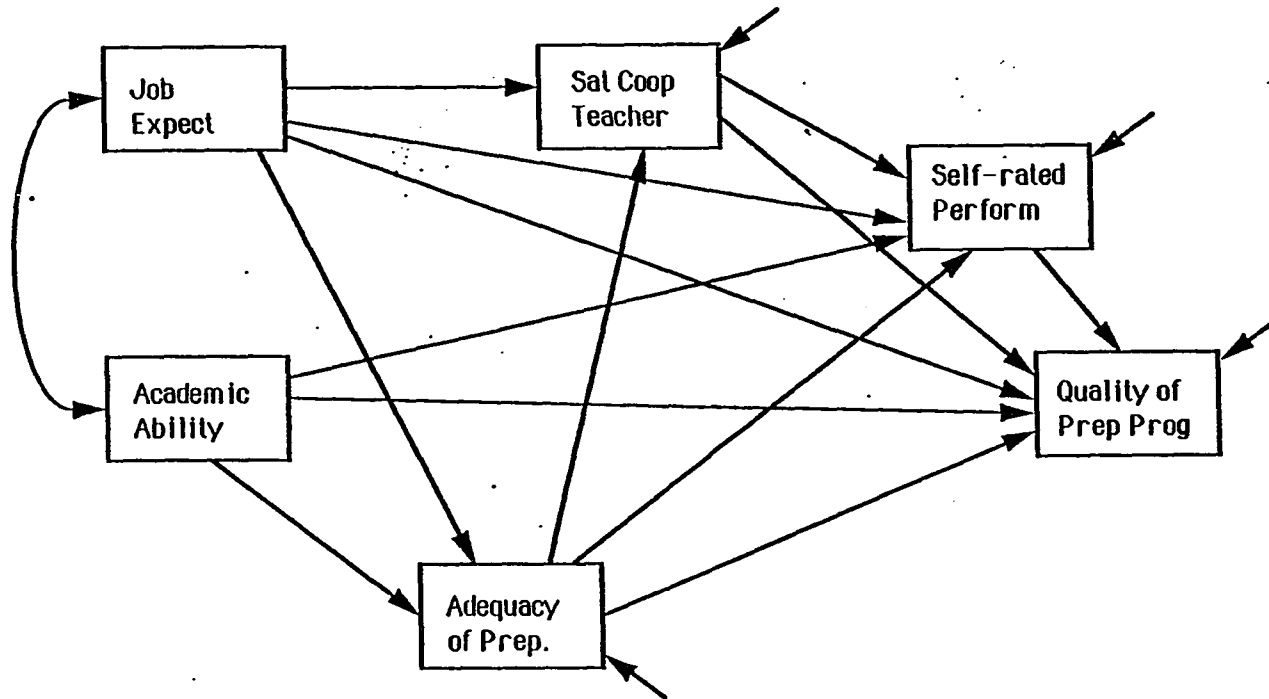


Figure 2.3. Model I: Single indicator model with no measurement error

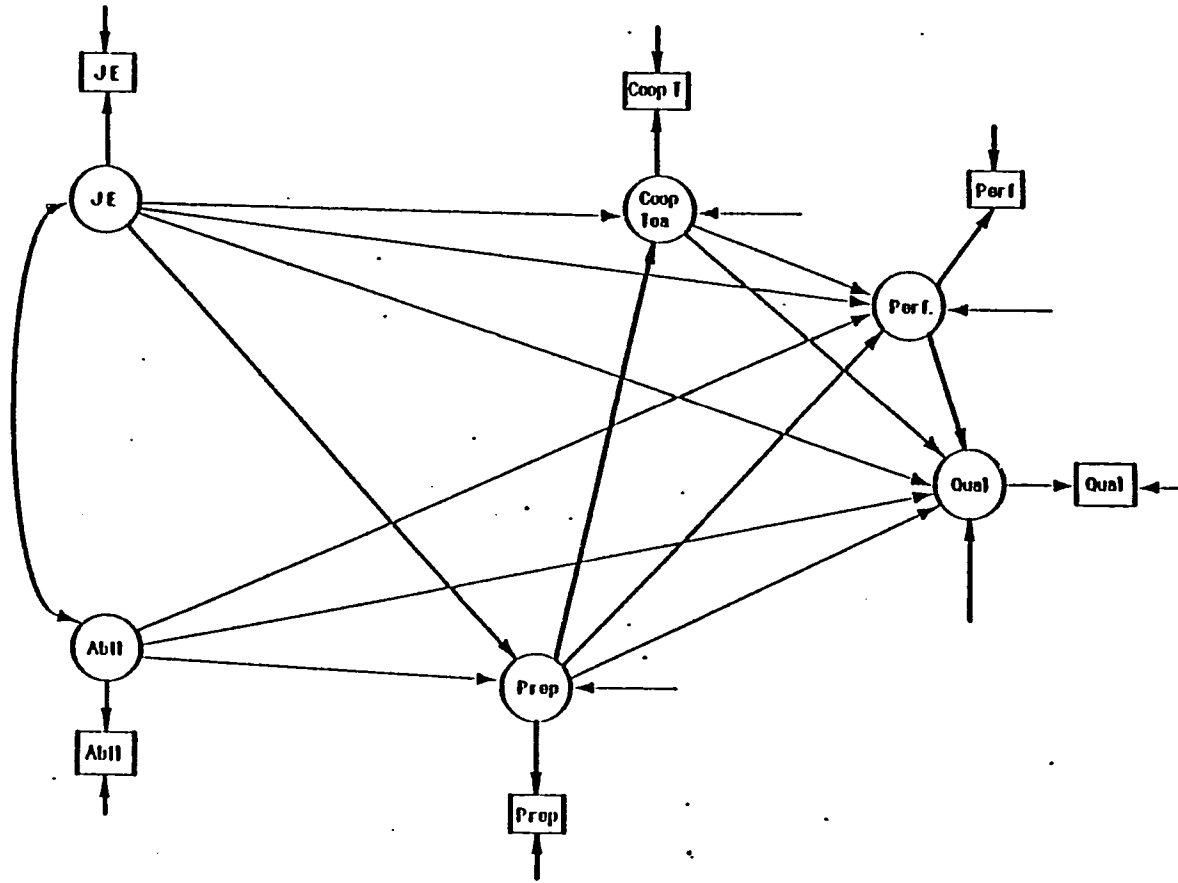


Figure 2.4. Model II: Single indicator model with adjustment for measurement error

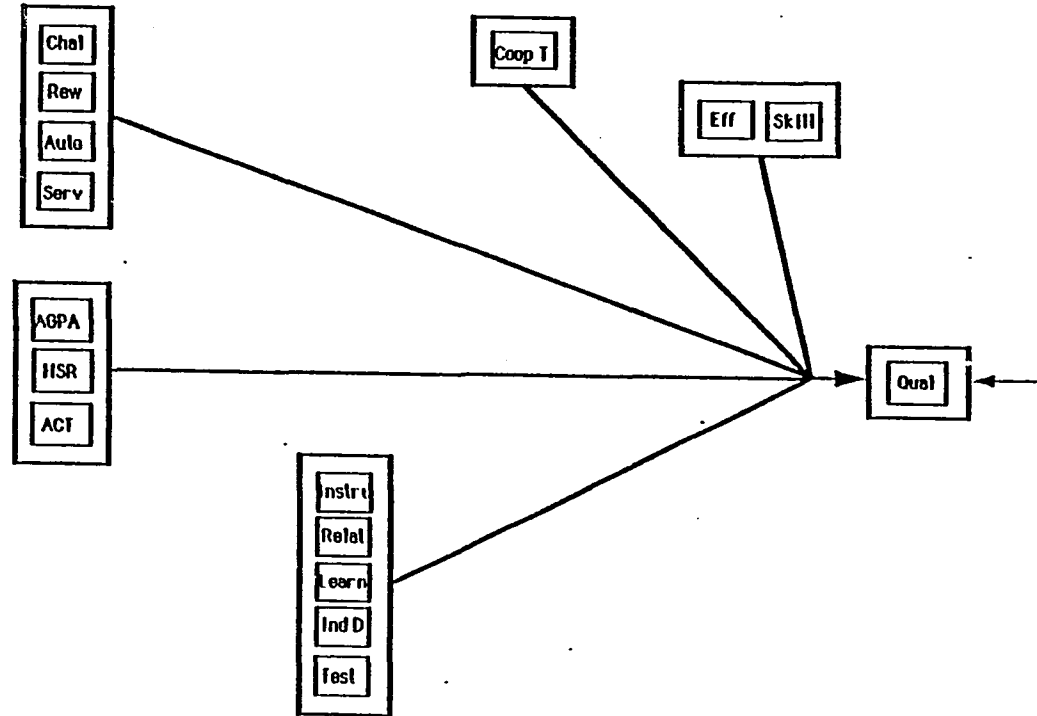


Figure 2.5. Model III: Multiple indicator model with no measurement error

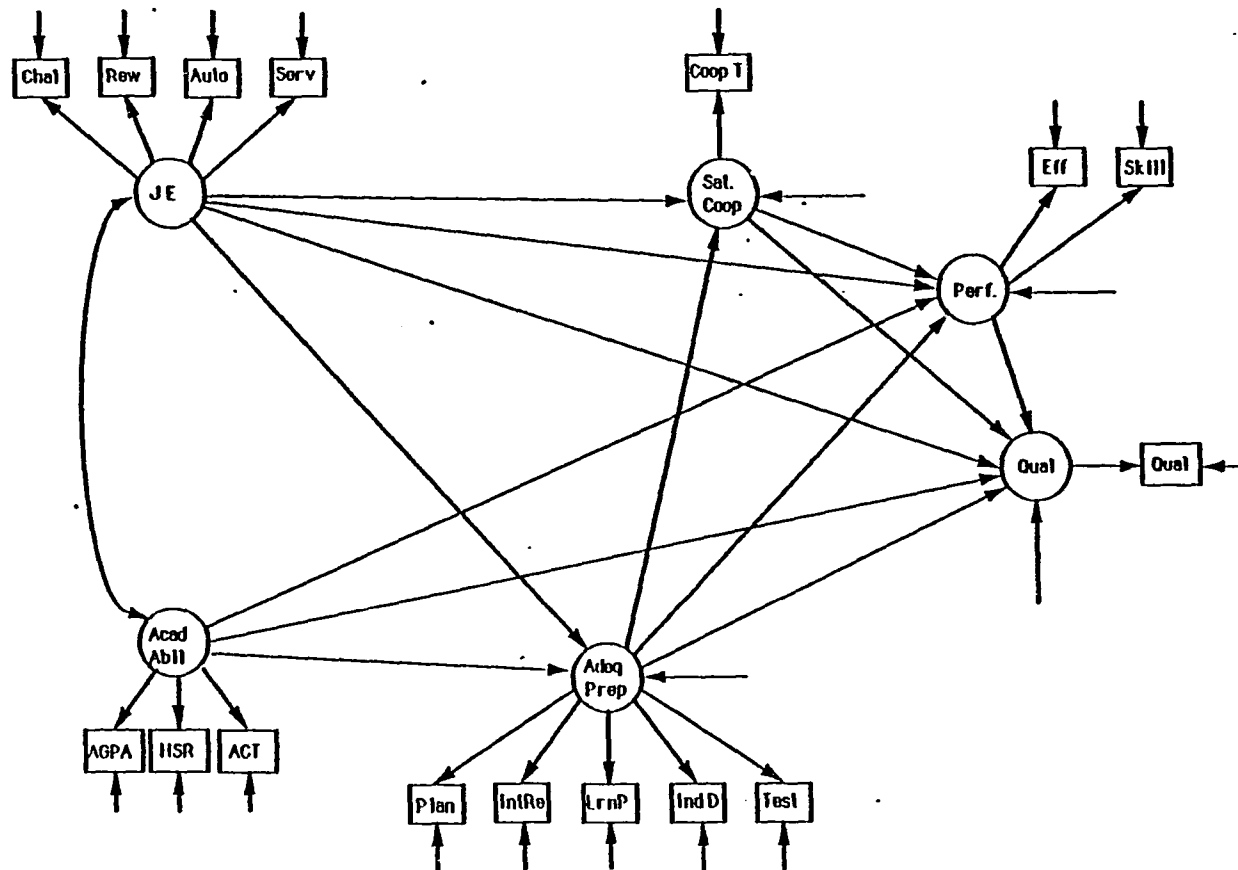


Figure 2.6. Model IV: Multiple indicator model with adjustment for measurement error

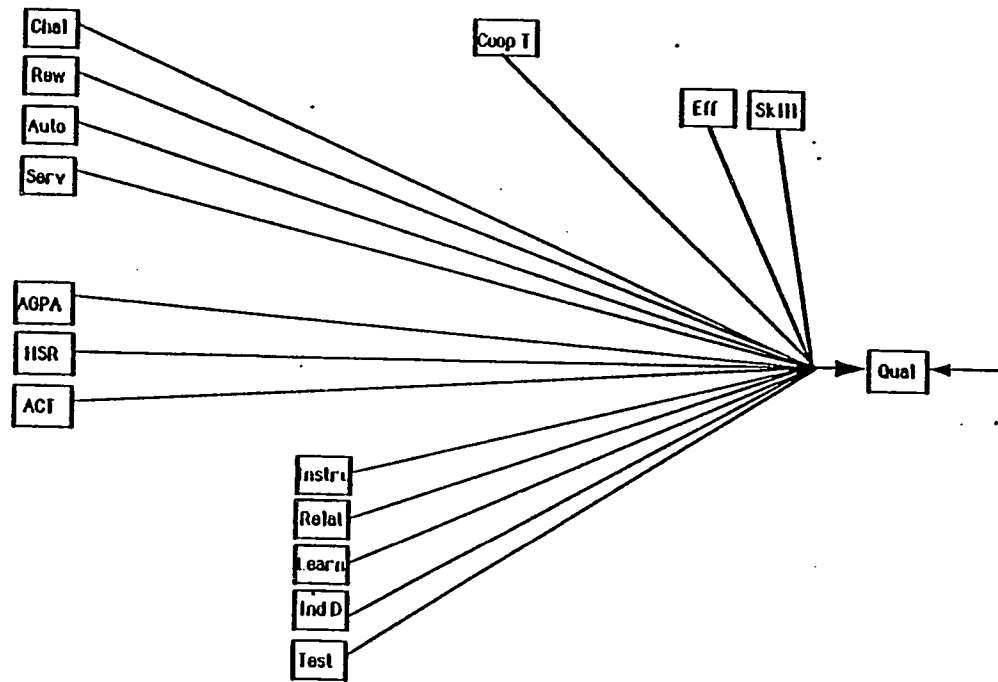


Figure 2.7. Model V: Single variable model with no measurement error

CHAPTER 3 METHODOLOGY

This study was designed to examine methods of analyzing structural equation models under alternative assumptions and measurement conditions involving preservice teacher education variables. This chapter will describe the data source and procedures, the population and sample, the instrument used, and the analytic methods.

Data Source and Procedures

A comprehensive longitudinal model to evaluate and improve the teacher education program at Iowa State University was initiated in 1979 by the Research Institute for Studies in Education (RISE). RISE collects relevant information concerning personal characteristics, competencies, attitudes, and career paths of Iowa State University preservice teachers and teacher education graduates (Research Institute for Studies in Education, 1988).

This longitudinal model specifies the collection of data at four different times. Students are first surveyed while enrolled in a beginning teacher education course with the second survey point at semester of graduation. Teacher education graduates are then surveyed at one and five years following graduation using procedures for mail surveys recommended by Dillman (1978).

Information for this study was gathered from graduating students that had completed the teacher education program during the fall and

spring semesters of the 1986-87 and 1987-88 school years. Approval from the Use of Human Subjects in Research had been received for all questionnaires used in this RISE project.

Subjects

The target population was the fall and spring teacher education graduates for the 1986-87 and 1987-88 school years. From the population of 703 graduates, completed questionnaires were received from 420 respondents. Gender and teaching level information of the respondents is presented in Table 3.1.

Table 3.1. Gender and teaching level of respondents

Characteristics	Number	Adjusted Percent
Sex		
Female	339	80.7
Male	81	19.3
	---	-----
	420	100.0
Teaching level		
Elementary	241	57.4
Secondary	179	42.6
	---	-----
	420	100.0
Teaching level	Number	Adjusted Percent
Elementary		
Female	231	55.0
Male	10	2.4
Secondary		
Female	108	25.7
Male	71	16.9
	---	-----
	420	100.0

Instrumentation

The Teacher Education Program Graduate Survey (see Appendix A) developed by RISE personnel was used to collect data for this study. Survey items providing relevant information for this study focused on the areas of job expectations, perceived adequacy of pre-student teaching preparation, satisfaction with the student teaching cooperating teacher, self-rating of student teaching behaviors, and overall quality of teacher preparation. Information used to measure academic ability was collected from the permanent records of the Admissions and Records Office and College of Education Student Services Office.

For this study, respondents' academic ability was measured by grade point average at the time of admittance to the teacher education program, high school rank, and ACT composite score. The high school rank data were recalculated with a linear transformation so that a large number indicated a high ranking and a small number indicated a low ranking. The measures were standardized because of the wide variety of scales involved. For the Models I and II, academic ability was computed as a composite mean of the three measures. The three measures served as exogenous variables in Model III and as indicators for the academic ability latent variable in Model IV. Table 3.2 contains respondent information regarding the three academic ability measures.

Job expectations were measured by four factorally and conceptually derived scales indicating how important it is that a job provide specific characteristics (Warren & Kemis, 1989). The four scales were

Table 3.2. Academic ability descriptive statistics

Scale	N	Raw Score		Standardized	
		Mean	S.D.	Mean	S.D.
Admit grade point average	271	2.90	.450	.000	.999
High school rank	271	78.56	17.032	.000	1.000
ACT composite score	271	22.27	4.178	.000	1.000

challenge/responsibility, extrinsic reward, autonomy, and serve/help others. For Models I and II, a single indicator was formed by computing the composite mean of the four standardized scales. The four scales served as exogenous variables in Model III and multiple indicators for the latent job expectation variable in Model IV. Table 3.3 contains descriptive information regarding the job expectation items.

Table 3.3. Job expectations descriptive statistics

Scale	N	Mean ^a	S.D.
Challenge/Responsibility	271	4.20	.488
Extrinsic Reward	271	3.86	.574
Autonomy	271	4.40	.433
Service/Help	271	4.42	.486

^a 5 = very important to 1 = very unimportant.

For perceived adequacy of pre-student teaching preparation, respondents rated their professional education preparation program in five factorally and conceptually derived areas (Warren & Kemis, 1989). Descriptive statistics for adequacy of pre-student teaching preparation scales are presented in Table 3.4. For Models I and II, adequacy of pre-student preparation was computed as a composite mean of standardized scales listed in Table 3.4. The five scales served as a block of endogenous variables in Model III and multiple indicators of the adequacy of preparation latent variable in Model IV.

Table 3.4. Adequacy of preparation descriptive statistics

Scale	N	Mean ^a	S.D.
Planning and delivering instruction	271	3.69	.606
Interpersonal relationships	271	3.21	.688
Assessing/dealing with learning problems	271	3.21	.828
Providing for individual differences	271	4.01	.790
Testing/evaluating student achievement	271	3.43	.818

^a5 = very adequate preparation to 1 = very inadequate preparation.

For satisfaction with cooperating teacher, respondents were asked to rate their satisfaction (5=high, 1=low) with the assigned cooperating teacher. This item (mean = 4.48, standard deviation = .811) served as a single indicator in all four models.

The self-rated student teaching behavior was measured by two

factorally and conceptually derived scales regarding respondents' perceived performance of teaching behaviors in specified areas (see Table 3.5 for descriptive information). In Models I and II, this variable was computed as a composite mean of the two standardized scales listed in Table 3.5. Both scales served as endogenous variables in Model III and multiple indicators for the self-rated performance latent variable in Model IV.

Table 3.5. Self-rated student teacher behavior descriptive statistics

Scale	N	Mean ^a	S.D.
Teaching effectiveness	271	8.37	.953
Teaching skills	271	8.33	.958

^a10 = very high performance of behavior to 0 = very low performance of behavior.

For the quality of preparation variable, respondents were asked to rate the quality of their Teacher Preparation Program at Iowa State University (10=very high, 0=very poor). This item (mean = 6.88, standard deviation = 1.737) measured the quality of preparation variable in all four models.

Table 3.6 contains standardized descriptive statistics used for Models I and II.

Correlations for Model I and Model II variables are listed in Table 3.7. Correlations for the variables in Models III and IV are listed in Table 3.8.

Table 3.6. Standardized composite descriptive statistics for variables used in Models I and II

Variable	Number of scales combined	Mean	S.D.	Alpha
Job expectation	4	.028	.769	.75
Academic ability	3	.000	.819	.75
Adequacy of preparation	5	.028	.769	.78
Self-rated performance	2	-.016	.897	.87

Table 3.7. Correlations for Models I and II (N = 271)

	1	2	3	4	5	6
1	1.00					
2	.09	1.00				
3	.28 *	.19 *	1.000			
4	.56 **	.15 *	.23 *	1.00		
5	.18 *	.09	.51 **	.12 **	1.00	
6	-.03	-.02	-.08	-.05	-.10	1.00

1 = Adequacy of preparation
 2 = Satisfaction with cooperating teacher
 3 = Self-rated teaching performance
 4 = Quality of preparation
 5 = Job expectation
 6 = Academic ability

* $p < .05$.

** $p < .01$.

Table 3.8. Correlations for Models III, IV, and V (N = 271)

	1	2	3	4	5	6	7	8
1	1.00							
2	.57**	1.00						
3	.45**	.47**	1.00					
4	.36**	.29**	.25**	1.00				
5	.56**	.43**	.46**	.27**	1.00			
6	.11	.05	.05	.06	.06	1.00		
7	.33**	.18**	.19**	.10	.19**	.23**	1.00	
8	.31**	.18**	.16**	.10	.20**	.13*	.75**	1.00
9	.59**	.35**	.35**	.35**	.40**	.15*	.22**	.20**
10	.18**	.13*	.06	.00	.08	.08	.44**	.36**
11	.05	.06	.10	-.02	.09	-.07	.25**	.24**
12	.21**	.14*	.11	.12*	.11	.16*	.44**	.41**
13	.21**	.10	.16**	.04	.07	.12	.43**	.34**
14	.04	-.02	-.02	.12*	.04	-.02	-.04	.03
15	-.07	-.04	-.09	.07	-.02	-.02	-.02	.08
16	-.15*	-.03	-.11	-.01	.01	-.01	-.24**	-.14
	9	10	11	12	13	14	15	16
9	1.00							
10	.11	1.00						
11	.07	.50**	1.00					
12	.07	.53**	.36**	1.00				
13	.09	.55**	.21**	.43**	1.00			
14	.09	-.01	-.17**	-.04	.05	1.00		
15	-.07	.03	-.13*	.02	-.03	.47**	1.00	
16	-.14*	-.09	-.23**	-.10	-.09	.46**	-.59**	1.00
1 = Plan/deliver instruction	9 = Quality of preparation							
2 = Interpersonal relations	10 = Challenge/responsibility							
3 = Learning problems	11 = Extrinsic rewards							
4 = Provide for individual diff.	12 = Autonomy							
5 = Testing/evaluating	13 = Help/serve							
6 = Coop. teacher satisfaction	14 = Admit GPA							
7 = Environment for learning	15 = High school rank							
8 = Teaching skills	16 = ACT							

Analysis of Data

Parameter estimates for models without adjustment for measurement error (Models I, III, and V) were computed using regression procedures of the Statistical Package for the Social Sciences (SPSSX) (SPSSX, 1986). Only the last structural equation (quality of preparation as the dependent variable) parameters were computed for Models III and V. Estimates for models with adjustment for measurement error (Models II and IV) were computed using the LISREL VI (Joreskog et al., 1984) program option within SPSSX.

When specifying a LISREL model, relationships between each pair of variables must be identified as none, correlated, or causal. This is done by specifying the elements of eight matrices which form the structural and measurement components of the model under consideration. Four of the matrices specify causation (Beta, Gamma) and measurement (Lambda-Y, Lambda-X). The other four (Psi, Phi, Theta-epsilon, and Theta-delta) are used to specify relationships between pairs of variables that may be correlated but have no specified causal link.

For Models II and IV, the structural equation portion using LISREL notation is

$$\begin{array}{c}
 \text{Beta} \\
 \text{-----} \\
 \begin{bmatrix} \eta_1 \\ \eta_2 \\ \eta_3 \\ \eta_4 \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 & 0 \\ \beta_{21} & 0 & 0 & 0 \\ \beta_{31} & \beta_{32} & 0 & 0 \\ \beta_{41} & \beta_{42} & \beta_{43} & 0 \end{bmatrix} \begin{bmatrix} \eta_1 \\ \eta_2 \\ \eta_3 \\ \eta_4 \end{bmatrix} + \begin{array}{c} \text{Gamma} \\ \text{-----} \\ \begin{bmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & 0 \\ \gamma_{31} & \gamma_{32} \\ \gamma_{41} & \gamma_{42} \end{bmatrix} \begin{bmatrix} \xi_1 \\ \xi_2 \\ \xi_2 \end{bmatrix} + \begin{bmatrix} \zeta_1 \\ \zeta_2 \\ \zeta_3 \\ \zeta_4 \end{bmatrix}
 \end{array}
 \end{array}$$

Nonzero elements specify direct effects of endogenous variables on endogenous variables (Beta matrix) and direct effects of exogenous variables on endogenous variables (Gamma matrix). The zero elements indicate no relationship between pairs of variables. It should be noted that the zero element in the Gamma matrix is the hypothesized noncausal relationship between academic ability and satisfaction with cooperating teacher. The ζ 's represent errors in equations.

Two other matrices must be specified using information from the structural equation component, Psi and Phi. Psi is a 4 by 4 (four endogenous variables) diagonal matrix indicating that errors in equations (ζ 's) are not correlated with each other. Phi is a 2 by 2 matrix (two exogenous variables) indicating the correlations between exogenous variables.

The measurement component for Model II is

$$\begin{array}{c} \text{Lambda-Y} \\ \text{-----} \\ \begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \eta_1 \\ \eta_2 \\ \eta_3 \\ \eta_4 \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ \epsilon_3 \\ \epsilon_4 \end{bmatrix} \\ \text{and} \end{array}$$

$$\begin{array}{c} \text{Lambda-X} \\ \text{-----} \\ \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \xi_1 \\ \xi_2 \end{bmatrix} + \begin{bmatrix} \delta_1 \\ \delta_2 \end{bmatrix} \end{array}$$

Lambda-Y specifies the measurement of endogenous variables while Lambda-X does the same for exogenous variables. Since each latent variable in the model has only one indicator, the 1's in Lambda-Y and Lambda-X serve a dual purpose. First, it allows the model to be identified so that a solution may be determined. Second, it sets the scale of the latent variable to that of the observed variable. The epsilons and deltas represent measurement error. If the epsilons and deltas were set to zero, there would be no measurement error and the observed and latent variables would be identical. A measurement model in this form would yield identical results to those of Model I. To adjust for measurement error, computed values based on observed variable variance and reliability are provided as input to the LISREL analysis.

The measurement portion of Model IV is

$$\begin{array}{c}
 \text{-----} \\
 \text{Lambda-Y} \\
 \text{-----}
 \end{array}
 \begin{array}{c}
 \left[\begin{array}{c} y_1 \\ y_2 \\ y_3 \\ y_4 \\ y_5 \\ y_6 \\ y_7 \\ y_8 \\ y_9 \end{array} \right] = \left[\begin{array}{cccc} 1 & 0 & 0 & 0 \\ \lambda_{21} & 0 & 0 & 0 \\ \lambda_{31} & 0 & 0 & 0 \\ \lambda_{41} & 0 & 0 & 0 \\ \lambda_{51} & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & \lambda_{83} & 0 \\ 0 & 0 & 0 & 1 \end{array} \right] \left[\begin{array}{c} \eta_1 \\ \eta_2 \\ \eta_3 \\ \eta_4 \end{array} \right] + \left[\begin{array}{c} \epsilon_1 \\ \epsilon_2 \\ \epsilon_3 \\ \epsilon_4 \\ \epsilon_5 \\ \epsilon_6 \\ \epsilon_7 \\ \epsilon_8 \\ \epsilon_9 \end{array} \right]
 \end{array}$$

and

$$\begin{array}{c}
 \text{Lambda-X} \\
 \text{-----} \\
 \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \\ x_6 \\ x_7 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ \lambda_{21} & 0 \\ \lambda_{31} & 0 \\ \lambda_{41} & 0 \\ 0 & \lambda_{52} \\ 0 & \lambda_{62} \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \end{bmatrix} + \begin{bmatrix} \delta_1 \\ \delta_2 \\ \delta_3 \\ \delta_4 \\ \delta_5 \\ \delta_6 \\ \delta_7 \end{bmatrix} .
 \end{array}$$

These measurement components have been expanded to allow for multiple indicators of latent variables. The 1's, epsilons, and deltas serve the same purposes as stated above for Model II. The other nonzero elements in Lambda-Y and Lambda-X are free to be computed in the designated scale.

The last two matrices to be specified are Theta-epsilon and Theta-delta. For Model IV, Theta-epsilon is a 9 by 9 diagonal matrix indicating uncorrelated errors. Similarly, Theta-delta is a 7 by 7 diagonal matrix.

The assessment of Model I included the R square value and a goodness of fit test for an overidentified model with uncorrelated residuals (Specht, 1975). Specht's method utilizes values determined by the overidentified model to be tested and values from the same model, but modified to be fully recursive. Results yield a chi square value

with degrees of freedom equal to the number of overidentifying restrictions (number of paths hypothesized to be zero in the overidentified model).

The assessments for Models II and IV were based on the chi square likelihood ratio test, goodness of fit index (GFI), adjusted goodness of fit index (AGFI), root mean squared residual (RMR), and Hoelter's critical N test. The analyses for Models III and V were restricted to a single structural equation involving the overall dependent variable (quality of teacher education program) thereby not allowing complete assessments.

CHAPTER 4

RESULTS

This chapter presents results of the analyses of five structural equation models developed under alternative assumptions and conditions. Model I is a six variable model with each variable measured by a single indicator under the assumption of no measurement error. Model II is the same as Model I except an adjustment was made for measurement error. Model III is a multiple indicator model assuming no measurement error. Model IV contains multiple indicators for latent variables and allows for measurement error in the indicators. Model V is a 16-variable model assuming no measurement error.

Table 4.1 lists the variable names and descriptions used in this chapter.

Table 4.2 lists descriptive statistics for the variables of Models I and II. The values for these variables were computed as composites of the observed variables for Models III and IV (see Table 4.1). The standardized means and standard deviations for Table 4.2 were computed as composites of standardized variables which caused slight deviations from expected standardized values for means (0.00) and standard deviations (1.000).

Table 4.1. Variable names and descriptions

Observed variables for Models I and II

<u>Name</u>	<u>Description</u>
PREP	Adequacy of preparation
SCOOP	Satisfaction with cooperating teacher
PERF	Self-rated performance of specified teaching behaviors
QUAL	Quality of teacher preparation program
JOB	Job expectations
ACAD	Academic ability

Observed variables for Models III, IV, and V

<u>Name</u>	<u>Description</u>
PLAN	Planning/delivering instruction
INTREL	Interpersonal relationships
LRNPROB	Recognize and deal with learning problems
INDIFF	Recognize and deal with individual differences
TEST	Test/evaluate student progress
SCOOP	Satisfaction with cooperating teacher
PERFA	Self-rated performance of teaching efficacy
PERFC	Self-rated performance of teaching skills
QUAL	Quality of teacher preparation program
CHAL	Challenge/responsibility of job
REWA	Extrinsic rewards (salary, status, security)
AUTO	Free to be creative, use special abilities

Table 4.1. (continued)

SERV	Serve others
AGPA	Admit grade point average
HSR	High school rank
ACT	ACT composite score

Table 4.2. Means and standard deviations for Models I and II
(N = 271)

Variable	Raw Score		Standardized	
	Mean	S.D.	Mean	S.D.
PREP	3.51	.539	.028	.769
SCOOP	4.48	.811	.000	1.000
PERF	8.35	.984	-.016	.897
QUAL	6.88	1.737	.000	1.000
JOB	4.22	0.373	.028	.769
ACAD	34.58	6.668	.000	.819

Table 4.3 contains the listwise correlations used for input for the Model II analysis. The endogenous variables PREP, SCOOP, and PERF are significantly correlated with the dependent variable QUAL. JOB is the only exogenous variable that is significantly related to QUAL. The exogenous variable ACAD has insignificant negative correlations with all variables.

Table 4.3. Correlations for Models I and II (N = 271).

	PREP	SCOOP	PERF	QUAL	JOB	ACAD
PREP	1.00					
SCOOP	.09	1.00				
PERF	.28**	.19*	1.00			
QUAL	.56**	.15*	.23**	1.00		
JOB	.18*	.09	.51**	.12*	1.00	
ACAD	-.03	-.02	-.08	-.05	-.10	1.00

* p < .05.

**p < .01.

Single Indicator Model with No Measurement Error (Model I)

Table 4.4 lists the standardized parameter estimates for Model I using multiple linear regression. The R square value is 0.331 implying that approximately 33 percent of QUAL variance is explained by the model. Five of the 13 hypothesized paths were significant. Among endogenous variables, the significant paths were PREP to PERF, PREP to QUAL, SCOOP to PERF. For the exogenous variables, JOB had the remaining two significant paths, one to PREP and the other to PERF.

Specht's (1975) method for calculating a chi-square value directly from residuals for overidentified models was used to test the fit of Model I. The formulas led to a nonsignificant chi-square value of 0.42 with 1 degree of freedom. This implies that Model I provides an acceptable fit of the data.

Table 4.4. Model I parameter estimates assuming no measurement error
(N = 271)

Path		Standardized
From	To	Parameter
PREP	SCOOP	.077
PREP	PERF	.187 ***
PREP	QUAL	.540 ***
SCOOP	PERF	.132 *
SCOOP	QUAL	.090
PERF	QUAL	.069
JOB	PREP	.181 ***
JOB	SCOOP	.080
JOB	PERF	.462 ***
JOB	QUAL	-.029
ACAD	PREP	-.011
ACAD	SCOOP	.000 ^a
ACAD	PERF	-.017
ACAD	QUAL	-.030

^a Hypothesized to be 0.

* p < .05.

***p < .001.

Single Indicator Model with Adjustment for Measurement Error
(Model II)

Model II analyzed the same data and variables as Model I but allowed for measurement error. LISREL VI was used to estimate Model II parameters. Table 4.5 contains estimated error values used for input in the analysis of Model II. Error values were approximated by multiplying the variance of each variable by the amount of estimated error (1 - reliability) (Hayduk, 1987, p. 119). Reliabilities for SCOOP and QUAL

were estimated using Winer's (1962, p. 126) formula for single item reliability. Both single item reliability estimates were computed to be .60.

Table 4.5. Error estimates for Model II (N = 271)

Variable	Standardized Variance	1 - Reliability	Estimated error
PREP	0.4918	0.18	0.0885
SCOOP	1.0000	0.40	0.4000
PERF	0.8050	0.14	0.1127
QUAL	1.0000	0.40	0.4000
JOB	0.5915	0.25	0.1479
ACAD	0.6708	0.25	0.1677

Parameter estimates for Model II adjusting for measurement error are listed in Table 4.6. Differences in model parameters range from .001 for the ACAD to PREP parameter to .078 for the SCOOP to PERF parameter. Model II values are larger than corresponding Model I values except for PREP to PERF, JOB to QUAL, ACAD to PREP, and ACAD to PERF.

Model II has the same significant paths as Model I. Of the five significant parameters, Model II values were larger than Model I values except for PREP to PERF. Two parameters (SCOOP to PERF and JOB to PERF) have large differences and one (PREP to PERF) differs very little.

Table 4.6. Model II parameter estimates with adjustment for measurement error (N = 271)

Path From	To	Model II Standardized Parameters
PREP	SCOOP	.082
PREP	PERF	.183 **
PREP	QUAL	.593 ***
SCOOP	PERF	.210 *
SCOOP	QUAL	.148
PERF	QUAL	.057
JOB	PREP	.213 **
JOB	SCOOP	.094
JOB	PERF	.535 ***
JOB	QUAL	-.046
ACAD	PREP	-.010
ACAD	SCOOP	.000 ^a
ACAD	PERF	-.010
ACAD	QUAL	-.036

^aHypothesized to be 0.

* p < .05.

** p < .01.

***p < .001.

Table 4.7 lists the R square values for Models I and II. As expected when adjusting for measurement error, Model II R square values increased for each endogenous variable. Measurement error is known to attenuate R square values (Pedhazur, 1982). Results displayed in Table 4.7 reflect this.

Table 4.7. Comparison of R square values for endogenous variables for Models I and II (N = 271)

Endogenous variable	R square	
	Model I	Model II
PREP	.033	.128
SCOOP	.015	.416
PERF	.316	.479
QUAL	.331	.766

The chi square value with 1 df is 0.03 ($p < .86$) indicating the model is a good fit. The R square value for QUAL in Model II indicates approximately 77 percent of QUAL's variance is explained. The Goodness of Fit Index (GFI) and the Adjusted Goodness of Fit Index (AGFI) are both 1.00. The closer the GFI and AGFI are to one, the better the fit. Also, a Root Mean squared Residual (RMR) value close to zero (.005 for Model II) indicates a good fit.

An alternative fit index, Hoelter's (1983) Critical N (CN), was also computed for Model II. Hoelter states that the CN value should be larger than 200 times the number of groups analyzed in order to have a good fit. Hoelter's CN formula is

$$CN = \frac{(z + \sqrt{2 \text{ df} - 1})^2}{2 \times 2} + G$$

$$\frac{(N - G)}{(N - G)}$$

where z = z-value for a specified alpha level,

df = degrees of freedom,

χ^2 = chi square value,

N = sample size,

and G = number of groups analyzed.

For Model II with an alpha of .05, the values are

$z = 1.65$, $df = 1$, $\chi^2 = .03$, $N = 271$, and $G = 1$.

These values yield a CN of 31,602, well above the required $200 \times 1 = 200$ necessary for a good fit.

Multiple Indicator Model with No Adjustment for Measurement Error
(Model III)

Model III is a block recursive model for multiple indicators. The observed variables are grouped into sets of variables which serve as indicators of an unobserved variable. This approach uses correlation, partial correlation, and multiple partial correlation to test predictions and/or assumptions in the assessment of a causal model. Because of the complexity involving this method, only the structural equation involving the overall dependent variable (QUAL) will be analyzed using multiple regression and assuming no measurement error.

Observed variable means and standard deviations are listed in Table 4.8 for Model III. These indicators are also used in the analyses of Models IV and V.

Table 4.8. Means and standard deviations of observed variables for multiple indicator Models III, IV, and V

Observed Variables	Raw Score		Standardized	
	Mean	S.D.	Mean	S.D.
PREP Set				
PLAN	3.69	.623	-.008	.972
INTREL	3.20	.727	.005	.946
LRNPROB	3.22	.854	-.009	.969
INDIFFS	4.01	.823	.005	.959
TEST	3.41	.839	.026	.975
SCOOP Set				
SCOOP	4.48	.811	.000	1.000
PERF Set				
PERFA	8.38	.990	-.019	.962
PERFC	8.35	1.002	-.013	.956
QUAL Set				
QUAL	6.88	1.737	.000	1.000
JOB Set				
CHAL	4.19	.474	.021	1.030
REWA	3.86	.554	-.006	1.035
AUTO	4.37	.443	.064	.977
SERV	4.40	.474	.034	1.026
ACAD Set				
AGPA	2.90	.450	.000	.999
HSR	78.56	17.032	.000	1.000
ACT	22.27	4.178	.000	1.000

Table 4.9 contains F-values used to determine if paths between each set of variables and QUAL are significant. These values were determined by the structural equation using QUAL as the dependent variable and all others as sets of independent variables. Multiple linear regression was used entering sets of indicator variables representing each of the five latent variables in the model.

Table 4.9. F values to determine significant paths for Model III
(N = 271)

Path		F value
From	To	
PREP	QUAL	$F(5, 255) = 27.56^{**}$
SCOOP	QUAL	$F(1, 255) = 4.16^*$
PERF	QUAL	$F(2, 255) = .16$
JOB	QUAL	$F(4, 255) = 1.82$
ACAD	QUAL	$F(3, 255) = 1.65$

* $p < .05$.

** $p < .01$.

Multiple Indicator Model with Adjustment for Measurement Error (Model IV)

Model IV specifies relationships among the latent variables, LJOB, LACAD, LPREP, LSCOOP, LPERF, and LQUAL. Multiple indicators were available for all latent variables except LSCOOP and LQUAL. The observed indicators are the same variables used for the sets in Model III (see Table 4.8). Table 4.10 lists the latent variables and their

indicators. Table 4.11 contains the correlations of observed variables used for input to analyze Model IV. LISREL VI was used to estimate Model IV parameters.

Table 4.10. Latent variables and indicators

Latent variable	Observed Indicator(s)
LPREP	PLAN, INTREL, LRNPROB, INDIFF, TEST
LSCOOP	SCOOP
LPERF	PERFA, PERFC
LQUAL	QUAL
LJOB	CHAL, REWA, AUTO, SERV
LACAD	AGPA, HSR, ACT

Reliability estimates for the two single indicators (SCOOP and QUAL) were estimated at .60. Measurement error for the other indicators was accounted for by the measurement component of the model. Table 4.12 contains Model IV structural equation parameter estimates allowing for measurement error. The γ_{ij} 's (beta matrix) represent effects of endogenous latent variables on endogenous variables while the γ_{ij} 's (gamma matrix) represent effects of exogenous variables on endogenous variables. The values in Table 4.12 represent relationships among latent (unobserved) variables.

Table 4.11. Multiple indicator correlations (N = 271).

	1	2	3	4	5	6	7	8	9	10	11	12
1	1.000											
2	.572	1.000										
3	.449	.473	1.000									
4	.360	.290	.248	1.000								
5	.557	.432	.455	.272	1.000							
6	.114	.053	.046	.064	.056	1.000						
7	.328	.179	.188	.104	.189	.321	1.000					
8	.308	.179	.157	.097	.202	.131	.750	1.000				
9	.595	.351	.350	.351	.398	.151	.225	.200	1.000			
10	.175	.134	.065	.007	.082	.083	.440	.363	.114	1.000		
11	.046	.059	.099	-.022	.089	-.066	.245	.239	.075	.502	1.000	
12	.215	.135	.112	.118	.108	.156	.437	.405	.067	.527	.361	1.000
13	.215	.099	.159	.044	.072	.118	.427	.338	.094	.546	.212	.429
14	.043	-.023	-.021	.120	.044	-.022	-.043	.028	.087	-.005	-.170	-.038
15	-.071	-.044	-.089	.066	-.020	-.020	-.020	.076	-.071	.035	-.128	.016
16	-.148	-.031	-.106	-.008	.015	-.014	-.243	-.139	-.139	-.090	-.233	-.097

- 1 = PLAN
- 2 = INTREL
- 3 = LRNPROB
- 4 = INDIFF
- 5 = TEST
- 6 = SCOOP
- 7 = PERFA
- 8 = PERFC
- 9 = QUAL
- 10 = CHAL
- 11 = REWA
- 12 = AUTO
- 13 = SERV
- 14 = AGPA
- 15 = HSR
- 16 = ACT

v = 271).

7	8	9	10	11	12	13	14	15	16
.000									
.750	1.000								
.225	.200	1.000							
.440	.363	.114	1.000						
.245	.239	.075	.502	1.000					
.437	.405	.067	.527	.361	1.000				
.427	.338	.094	.546	.212	.429	1.000			
.043	.028	.087	-.005	-.170	-.038	.055	1.000		
.020	.076	-.071	.035	-.128	.016	-.031	.470	1.000	
.243	-.139	-.139	-.090	-.233	-.097	-.090	.462	.587	1.000

Table 4.12. Model IV parameter estimates allowing for measurement error (N = 271)

Latent variables			
	From	Path TO	Standardized Parameter
β_{21}	PREP	SCOOP	.104
β_{31}	PREP	PERF	.218 **
β_{41}	PREP	QUAL	.750 ***
β_{32}	SCOOP	PERF	.233 **
β_{42}	SCOOP	QUAL	.140
β_{43}	PERF	QUAL	-.008
γ_{11}	JOB	PREP	.254 **
γ_{21}	JOB	SCOOP	.118
γ_{31}	JOB	PERF	.595 ***
γ_{41}	JOB	QUAL	-.057
γ_{12}	ACAD	PREP	-.076
γ_{22}	ACAD	SCOOP	.000 ^a
γ_{32}	ACAD	PERF	-.104
γ_{42}	ACAD	QUAL	-.049

^aHypothesized to be 0.

** p < .01.

***p < .001.

The R square value for LQUAL is .732, indicating that approximately 73 percent of the variance of this variable has been explained. This is approximately 4 percentage points less than explained variance of Model II (77%) and 21 percentage points more than Model III. The chi square value with 92 df is 173.56 ($p < .000$) indicating that the model is not a good fit. The GFI (.928) and RMR (.055) indicate a good fit, while the AGFI (.777) indicates a moderate fit. Computing Hoelter's CN with $z = 1.65$, $df = 92$, $\chi^2 = 173.56$, $N = 271$, and $G = 1$ yields $CN = 180$. This model test indicates that the model is not a good fit ($180 < 200 \times 1$).

Single Variable Model with No Measurement Value (Model V)

Model V represents, perhaps, the most common approach used in educational research to analyze structural equation models. All observed variables are entered into the regression analyses in a manner similar to that for Model I. Paralleling the analysis for Model III, the only structural equation analyzed for Model V involved QUAL as the dependent variable. Table 4.13 displays the standardized parameter estimates for the 15 independent variables for the analysis of Model V.

There were five significant paths linking to the QUAL variable. PLAN (planning/delivering instruction), INDIFF (providing for individual differences), SCOOP (satisfaction with cooperating teacher), and AGPA (admit grade point average) all had positive effects on quality of preparation program, while AUTO (freedom/can be creative) negatively affected QUAL.

This is the only model to have a significant result involving academic ability (AGPA). Also, no other model had a significant negative causal link (AUTO). Further, if the variables were viewed as sets, all sets except PERF had at least one significant causal link to QUAL.

Table 4.13. Model V parameter estimates for observed variables with no adjustment for measurement error (N = 271)

Variable	Standardized Parameter
PLAN	.470 ***
INTREL	-.027
LRNPROB	.079
INDIFF	.150 **
TEST	.061
SCOOP	.102 *
PERFA	.025
PERFC	.011
CHAL	.064
REWA	.066
AUTO	-.128 *
SERV	-.063
AGPA	.115 *
HSR	-.039
ACT	-.080

* p < .05.
 ** p < .01.
 ***p < .001.

Table 4.14 lists all of the observed and unobserved variables analyzed in the five models and the status of each variable's causal link to the overall dependent variable quality of preparation program

Table 4.14. Paths for quality of preparation structural equation as specified by five approaches

Variable		Model	Model	Model	Model	Model
Lat.	Obs.	I	II	III	IV	V
----	----					
PERF		NO ^a	NO	NO	NO	NA ^b
	PERFA	NA	NA	NA	NA	NO
	PERFC	NA	NA	NA	NA	NO
SCOOP		NO	NO	YES ^c	NO	YES
PREP		YES	YES	YES	YES	NA
	PLAN	NA	NA	NA	NA	YES
	INTREL	NA	NA	NA	NA	NO
	LRNPROB	NA	NA	NA	NA	NO
	INDIFF	NA	NA	NA	NA	YES
	TEST	NA	NA	NA	NA	NO
JOB		NO	NO	NO	NO	NA
	CHAL	NA	NA	NA	NA	NO
	REWA	NA	NA	NA	NA	NO
	AUTO	NA	NA	NA	NA	YES
	SERV	NA	NA	NA	NA	NO
ACAD		NO	NO	NO	NO	NA
	AGPA	NA	NA	NA	NA	YES
	HSR	NA	NA	NA	NA	NO
	ACT	NA	NA	NA	NA	NO

^aNO = Path is not significant.

^bNA = Not applicable.

^cYES = Path is significant.

(QUAL). This presentation of path status should clarify which paths are available for estimation by the various models. If the path could be estimated, a YES or NO was entered to indicate whether or not the path was important to the model. NA was entered to indicate that the path was not available for estimation for the specified model. It should be noted that although the variables listed in the Lat. column are designated as latent, they serve as observed variables for Models I and II.

Table 4.15 summarizes the path coefficient estimates for Models I, II, and IV (these paths were not available for Models III or V). It should be noted that values for Models I and II represent relationships between pairs of observed variables, while Model IV values represent relationships between pairs of latent variables.

Although the degree of significance varied slightly, all three models had the same statistically significant path coefficients (paths 2, 3, 4, 7, and 9). Except for path 2, the significant path coefficients increased in value from Model I to Model II to Model IV. In general, Model IV coefficients were larger (or more negative) than those of Models I and II. Largest differences occurred in paths 5, 11, and 13.

Table 4.16 lists the R square values for all models. R square values differ by only about 6 percent for Models I and III (no measurement error assumed). There is only about a 3 percent difference in the R square values for Models II and IV (adjusted for measurement error).

Table 4.15. Path coefficients for Models I, II, and IV (N = 271)

Path		Standardized parameters			
		Model I	Model II	Model IV	
From	TO				
1.	PREP	SCOOP	.077	.082	.104
2.	PREP	PERF	.187 ***	.183 **	.218 **
3.	PREP	QUAL	.540 ***	.593 ***	.750 ***
4.	SCOOP	PERF	.132 *	.210 *	.233 **
5.	SCOOP	QUAL	.090	.149	.140
6.	PERF	QUAL	.069	.056	-.008
7.	JOB	PREP	.181 ***	.213 **	.254 **
8.	JOB	SCOOP	.080	.094	.118
9.	JOB	PERF	.462 ***	.534 **	.595 ***
10.	JOB	QUAL	-.029	-.046	-.057
11.	ACAD	PREP	-.011	-.010	-.076
12.	ACAD	SCOOP	.000 ^a	.000 ^a	.000 ^a
14.	ACAD	PERF	-.017	-.010	-.104
15.	ACAD	QUAL	-.030	-.036	-.049

^aHypothesized to be 0.

* p < .05.

** p < .01.

***p < .001.

Contained in Appendix B is a summary list of suggested steps to structural equation model analysis. This list suggests which method could be utilized for analysis depending on assumptions and measurement conditions of the study.

Table 4.16. R square values for all models

Dependent Variable	R square values				
	Model I	Model II	Model III	Model IV	Model V
PREP	.033	.128	na ^a	.068	na
COOP	.015	.416	na	.036	na
PERF	.316	.471	na	.452	na
QUAL	.331	.766	.420	.732	.420

^ana = not available.

CHAPTER 5

SUMMARY/DISCUSSION AND RECOMMENDATIONS

This chapter presents a summary/discussion of the findings of this study followed by a list of recommendations for further research.

Summary/Discussion

The purposes of this study were to develop a structural equation model of preservice teacher variables and to examine alternative methods of testing this model under different assumptions and measurement conditions. A conceptual model was developed to examine teacher education program entrance variables, pre-student teaching adequacy of preparation, and post-student teaching ratings of supervision and self-rated performance. The overall dependent variable was a rating of the quality of the teacher preparation program. The sample for this research consisted of 420 Iowa State University teacher education graduates during the 1986/87 and 1987/88 school years.

The unobserved variables in the conceptual model were measured by 16 observed variables (indicators) which were standardized prior to analysis. Indicators for job expectations included challenge/responsibility, rewards, autonomy, and service to others. For academic ability, indicators were grade point average at the time of admittance to the teacher preparation program, high school rank, and ACT college entrance composite score. Pre-student teaching preparation indicators included planning/delivering instruction, interpersonal relationships,

diagnosing and dealing with learning problems, providing for individual differences, and testing/evaluating student progress. Self-rated student teaching performance had two indicators, teaching effectiveness and teaching skills. The variables of satisfaction with cooperating teacher and quality of preparation program each were measured by a single indicator.

Assumptions and measurement conditions for the analysis of data were altered to represent typical educational research situations leading to the development and analysis of four empirical models. Models I and II utilized single indicators computed as composite means of the respective observed standardized indicators. Model I assumed variables were measured without error. Model II utilized the same indicators as Model I, but adjustments were made to allow for measurement error. Models III and IV used the 16 standardized indicators without forming composites. Model III assumed no measurement error, while Model IV did allow for measurement error. The method of analysis for Models I and III was multiple linear regression. Models II and IV were analyzed using the LISREL approach.

Relative to the conceptual model, the primary hypothesis was that the quality of the teacher education program was directly affected by job expectations, academic ability, adequacy of pre-student teaching preparation, satisfaction with the cooperating teacher, and self-rated performance of student teaching. Results were obtained for this hypothesis for Models I, II, III, and IV. In all four models, the only causal link supported was the path from adequacy of pre-student teaching

preparation to quality of the education program. This result tends to indicate that teacher education graduates who perceive their pre-student teaching preparation as very adequate will generally feel that the quality of the teacher education program was high.

There were inconsistent results for the path from satisfaction with student teaching cooperating teacher to quality of the teacher preparation program. Results from Model III indicate this direct effect was significant, while the other model results did not. Because satisfaction with cooperating teacher was a single indicator variable, the path was also estimated in Model V. As in Model III, the path was significant. A closer inspection of the path test statistics for the five models revealed values were clustered about the .05 level of significance. Had the significance level been set at .10, the path would have been significant in the other three models.

A second hypothesis was that job expectations, academic ability, pre-student teaching preparation, and satisfaction with cooperating teacher directly affected the self-rated performance of student teaching. Results indicated that three of the hypothesized causal links were supported. First, satisfaction with cooperating teacher has a positive direct effect on self-rated student teaching performance. Thus, a high level of satisfaction with the cooperating teacher tends to increase the self-rating of student teaching performance. This supports claims that the cooperating teacher can influence the student teacher during the field experience. Second, self-rated student teaching performance was directly affected by perceived adequacy of preparation.

Last, the causal link from job expectations to self-rated teaching performance had a positive direct effect.

Also of interest was whether job expectations and pre-student teaching preparation directly affected satisfaction with cooperating teacher. No significant paths were found.

Finally, direct effects of job expectations and academic ability on pre-student teaching preparation were examined. Results indicated that only the job expectations variable had a significant direct effect on pre-student teaching preparation. This supports previous research that indicated individuals enter the teaching profession to work with children. Pre-student teaching preparation provides this as a central theme throughout.

In addition to the hypotheses regarding causal links, statistical tests for goodness of fit were made for Models I, II, and IV. Under the assumptions and conditions for these models, results indicated that Model IV did not provide a good fit of the data. However, both Models I and II did provide a satisfactory fit of the data, providing a possible explanation of the causal mechanism which produced the observable values.

Consideration of a reduced model with significant paths only has several implications for teacher education. First, the perceived adequacy of preparation (coursework prior to student teaching) has causal effects for both self-rated performance during student teaching and quality of preparation program. This provides support that pre-student teaching preparation is important to student teaching self-rated

performance and preparation program quality. Second, since self-rated performance does not have a significant causal effect on quality of preparation program, it appears that quality of preparation program is determined in terms of pre-student teaching coursework. Last, although the academic ability variable did not have significant causal effects on any other variables, grade point average at the time of admittance to the preparation program (Model III) did have a significant causal effect on quality of preparation program, indicating that respondents with high grade point averages when admitted to the preparation program tend to rate the quality of preparation program higher.

Although there were no statistical tests made to compare across models, some interesting observations can be made. First, there was a general consistency among Models I, II, III, and IV regarding the existence (and nonexistence) of causal links between pairs of variables. Since the approaches used are accepted methods of analysis for structural equation models, similar results for strong relationships should be expected across models.

Second, varying conditions of measurement error resulted in different parameter estimates among models. This also is expected, but is more difficult to assess. The effects of errors are "complicated" (Cochran, 1968, p. 655).

Starting with R square values, it is well known that measurement error in the independent variables and/or dependent variable leads to a downward bias in the estimate of R square. This was clearly evident by the results of this study. R square values for Models I and III (no

measurement error) were approximately half the R square values of Models II and IV (adjusted for measurement error), respectively. It is also known that measurement error in the independent variables in multiple regression may lead to either a downward or upward bias of path estimates. This bias was also confirmed in the estimation of path coefficients in Models I, II, and IV. However, it was observed that Model IV tended to have the largest parameter values (in absolute value) while the smallest parameter estimates tended to be in Model I. More specifically, Model IV parameters were larger (in absolute value) than all but one of the 13 estimated path values.

Third, many variables in educational research involve unobserved (latent) variables. With unobserved variables, it is not feasible to expect a single indicator to describe validly and reliably complex constructs such as ability, satisfaction, and quality. Instead, multiple indicators should be used and the method of LISREL applied.

Last, it is common in educational research to have very little of the variance of the endogenous variables explained. This can often be traced to measurement instruments that have low reliabilities. Further study of measurement errors is necessary in cases such as these.

Researchers need to know what statistical tools are available and under what conditions each method is used in order to analyze research data effectively. The methods of analysis used and discussed in this study provides a basis from which a sound research plan can be formulated for structural equation models. To assist researchers analyzing structural equation models, a summary guide in outline form

has been provided in Appendix B.

Recommendations for Future Research

Based on the findings and insights gained from this study, the following are recommendations for future research.

1. This study should be replicated using only those teacher education graduates that entered the teaching profession.
2. It is recommended that this study should be replicated with additional exogenous variables.
3. The conceptual model did not consider reciprocal relationships. It is suggested that additional research be done with Model IV to investigate the effects of reciprocal relations.
4. Additional research could be done comparing several groups of teacher education graduates. Of particular interest would be the comparison of groups determined by grade point average (high vs. low) and by level of teacher preparation (elementary vs. secondary).
5. Although variables in the conceptual model have a temporal ordering of occurrence, all data were collected at one time. It is suggested that this study be replicated with pre-student teaching variable data collected prior to student teaching to avoid possible confounding.
6. Student teaching performance was self-rated in this study. Data are becoming available that include performance ratings by both the cooperating teacher and university supervising teacher. Additional

research could incorporate these additional indicators of performance.

BIBLIOGRAPHY

- Adams, R. D. & Martray, C. R. (1980). Correlates of teacher perceived problems. Washington, DC: Rand Corporation.
- Alwin, D. F. & Hauser, R. M. (1975). The decomposition of effects in path analysis. American Sociological Review, 40, 37-47.
- Anderson, J. C. & Gerbing, D. W. (1984). The effect of sampling error on convergence, improper solutions and goodness-of-fit indices for maximum likelihood confirmatory factor analysis. Psychometrika, 49, 155-173.
- Appleberry, M. (1976). What did you learn from student teaching? Instructor, 85, 38-40.
- Asher, H. B. (1983). Causal Modeling. Beverly Hills: Sage.
- Ashton, P. T., Webb, R. B., & Doda, N. (1983). A study of teachers' sense of efficacy. (Report No. 400-79-0075). Gainesville, FL: University of Florida. (ERIC ED 231 833)
- Bentler, P. M. (1982). Multiple analysis with latent variables: Causal modeling. In C. Fornell (Ed.), A Second Generation of Multivariate Analysis, Vol. 1. New York: Praeger Publishers.
- Bentler, P. M. & Bonett, D. G. (1980). Significance tests and goodness of fit in the analysis of covariance structures. Psychological Bulletin, 88, 588-606.
- Blalock, H. M. (1961). Evaluating the relative importance of variables. American Sociological Review, 26, 866-874.
- Blalock, H. M. (1963). Correlated independent variables. American Journal of Sociology, 42, 233-237.
- Blalock, H. M. (1968). Theory building and causal inferences. In H. M. Blalock and A. B. Blalock (Eds.), Methodology in Social Research. New York: McGraw-Hill.
- Blalock, H. M. (1971). Causal Models in the Social Sciences. Chicago: Aldine-Atherton.
- Bollen, K. A. (1989). Structural Equations with Latent Variables. Unpublished manuscript. Department of Sociology, University of North Carolina, Chapel Hill.

- Book, C. & Freeman, D. (1986). Student expectations and teacher traditions with which we can live. Journal of Teacher Education, 34(1), 9-13.
- Boomsma, A. (1982). On the robustness of LISREL (Maximum likelihood estimation) against small sample sizes in factor analysis models. In K. Joreskog & H. Wold (Eds.), Systems Under Indirect Observation: Causality, Structure, Prediction, Part I. Amsterdam: North Holland Publishing Company.
- Borg, W. R. & Gall, M. D. (1983). Educational Research: An Introduction. New York: Longman.
- Boudon, R. (1965). A method of linear causal analysis: Dependence analysis. American Sociological Review, 30, 365-374.
- Brown, J. A. (1986). Principal practicum participants: Analysis of role perceptions. Paper presented at the Annual Meeting of the Canadian Society for the Study of Education, Winnipeg.
- Campbell, L. P. & Williamson, J. A. (1973). Practical problems in the student teaching cooperative teacher relationships. Education, 94, 168-169.
- Chapman, D. W. (1984). Teacher retention: The test of a model. American Educational Research Journal, 21(3), 645-658.
- Chapman, D. W. & Hutcheson, S. M. (1982). Attrition from teaching careers: A discriminant analysis. American Educational Research Journal, 75(21), 645-658.
- Chapman, D. W. & Lowther, M. A. (1982). Teachers' satisfaction with teaching. Journal of Educational Research, 75, 241-247.
- Chen, K. C. (1982). Characteristics associated with university teacher program applicants, graduates, and practicing teachers. Unpublished doctoral dissertation, Iowa State University, Ames, IA.
- Cochran, W. G. (1968). Errors of measurements in statistics. Technometrics, 10, 637-666.
- Cochran, W. G. (1970). Some effects of errors of measurement on multiple correlation. Journal of the American Statistical Association, 65, 22-34.
- Cohen, J. & Cohen, P. (1983). Applied multiple regression/correlation analysis for the behavioral sciences (2nd ed.). Hillsdale, NJ: Erlbaum.

- Darling-Hammond, L., Wise, A. E., & Pease, S. R. (1983). Teacher evaluation in the organizational context: A review of the literature. Review of Educational Research, 53, 285-328.
- Degracie, J. S. & Fuller, W. A. (1972). Estimation of the slope and analysis of covariance when the concomitant variable is measured with error. Journal of the American Statistical Association, 67, 930-937.
- Dillman, D. A. (1978). Mail and telephone surveys: The total design method. New York: Wiley.
- Duncan, O. D. (1966). Path analysis: Sociological examples. American Journal of Sociology, 72, 1-16.
- Duncan, O. D. (1975). Introduction to Structural Equation Models. New York: Academic Press.
- Ecob, R. & Cuttance, P. (1987). Structural Modeling by Example. New York: Cambridge University Press.
- Elmore, P. B. & Woehlke, P. L. (1988). Methods employed in American Educational Research Journal, Educational Researcher, and Review of Educational Research from 1978 to 1987. Educational Researcher, 25, 20-22.
- Fox, J. (1980). Effect analysis in structural equation models. Sociological Methods and Research, 9, 3-28.
- Frerichs, D. K., Kemis, M. R., & Crawford, R. M. (1989). Computations for path analysis. (Research report series). Iowa State University, Research Institute for Studies in Education, Ames.
- Fuller, W. A. & Hidiroglou, M. A. (1978). Regression estimation after correction for attenuation. Journal of the American Statistical Association, 73, 99-104.
- Goldberger, A. S. (1973). Structural equations: An overview. In A. Goldberger & O. Duncan (Eds.), Structural Equations in the Social Sciences. New York: Seminar Press.
- Guttman, L. (1977). What is not what in statistics? The Statistician, 26, 81-107.
- Guyton, E. & Farokhi, E. (1987). Relationships among academic performance, basic skills, subject matter knowledge, and teaching skills of teacher education graduates. Journal of Teacher Education, 38, 37-42.

- Hayduk, L. A. (1987). Structural Equation Modeling with LISREL. Baltimore: The Johns Hopkins University Press.
- Hays, W. L. (1982). Satisfaction with the student teaching experience: A multiple regression approach. (ERIC ED 223 571)
- Heffley, R. C. (1983). Factors affecting teacher turnover in Kansas. Unpublished doctoral dissertation, University of Kansas, Lawrence, Kansas.
- Heise, D. R. (1969). Problems in path analysis and causal inference. In E. Borgatta & G. Bohrnsted (Eds.), Sociological Methodology 1970. San Francisco: Jossey-Bass.
- Hill, R. J. (1970). On the relevance of methodology. In N. K. Denzin (Ed.), Sociological Methods. Chicago: Aldine Publishing Co.
- Hoelter, J. W. (1983). The analysis of covariance structures: Goodness of fit indices. Sociological Methods and Research, 11, 325-344.
- Isaacson, L. E. (1978). Career information in counseling and teaching (3rd ed.). Boston, MA: Allyn and Bacon, Inc.
- Joreskog, K. G. (1973). A general method for estimating a linear structural equation system. In A. Goldberger & O. Duncan (Eds.), Structural Equations in the Social Sciences. New York: Seminar Press.
- Joreskog, K. G. (1982). The LISREL approach to causal model building in the social sciences. In K. G. Joreskog & H. Wold (Eds.), Systems under Indirect Observations: Part I. Amsterdam: North-Holland.
- Joreskog, K. G. & Sorbom, D. (1986). LISREL VI: User's Guide. Mooresville, IN: Scientific Software, Inc.
- Keith, P. M., Warren, R. D., & Dilts, H. E. (1983). Teacher education graduates. Sex, career plans, and preferences for job factors. Urban Education, 18(3), 361-375.
- Keith, T. Z. (1988). Path analysis: An introduction for school psychologists. School Psychology Review, 17(2), 343-362.
- Kenny, D. A. (1979). Correlation and Causality. New York: Wiley-Interscience.
- Kerlinger, F. N. (1964). Foundations of Behavioral Research. New York: Holt, Rinehart and Winston, Inc.

- Kerr, D. H. (1983). Teaching competence and teacher education in the United States. In L. S. Shulman & G. Sykes (Eds.), Handbook of teaching and policy. New York: Longman.
- Long, J. S. (1981). Covariance Structure Models: An Introduction to LISREL. Beverly Hills: Sage.
- McPherson, J. M. (1976). Theory trimming. Social Science Research, 5, 95-105.
- Miller, A. D. (1971). Logic of causal analysis: From experimental to nonexperimental designs. In H. M. Blalock (Ed.), Causal Models in the Social Sciences. Chicago: Aldine-Atherton.
- Murphy, J. F. (1982). Why teachers drop out. Illinois Schools Journal, 61,(1-4), 35-41.
- Page, J., Page, F., & Million, S. (1983, April). Teacher education curricula: Perceptions of first-year teachers. Paper presented at the annual meeting of the American Educational Research Association, Montreal, Canada. (ERIC ED 229 364)
- Pedhazur, E. J. (1982). Multiple Regression in the Behavioral Sciences. New York: Holt, Rinehart, Winston.
- Plewis, I. (1985). Analysing change. New York: John Wiley & Sons.
- Porter, A. C. & Brophy, J. (1988). Synthesis of research on good teaching: Insights from the work of the institute for research on teaching. Educational Leadership, 45(8)74-85.
- Research Institute for Studies in Education. (1988). Profile VIII: Teacher education students (RISE Research Report No. 16). Ames, IA: Iowa State University.
- Rosenberg, M. (1968). The Logic of Survey Analysis. New York: Basic Books.
- Rosenholtz, S. J. (1989). Workplace conditions that affect teacher quality and commitment: Implications for teacher induction programs. The Elementary School Journal, 89(4), 421-439.
- Saris, W. E. & Stronkhorst, L. H. (1984). Causal Modeling in Nonexperimental Research. Amsterdam: Sociometric Research Foundation.

- Schalock, D. (1983). Methodological considerations in future research and development in teacher education. In K. P. Howey & W. E. Gardner (Eds.), The Education of Teachers: A Look Ahead (pp. 38-73). New York: Longman.
- Schuessler, K. (1971). Analyzing Social Data. Boston: Houghton Mifflin.
- Selltiz, C. (1959). Research Methods in Social Relations. New York: Holt, Rinehart, & Winston.
- Sikula, J. P. & Roth, R. A. (1984). Teacher preparation and certification: The call for reform. Bloomington, IN: Phi Delta Kappa Educational Foundation.
- Simon, H. A. (1954). Spurious correlation: A causal interpretation. Journal of the American Statistical Association, 49, 467-479.
- Sobel, M. E. (1987). Some new results on indirect effects and their standard errors in covariance structure models. In N. Tuma (Ed.), Sociological Methodology 1986. San Francisco: Jossey-Bass.
- Specht, D. A. (1975). On the evaluation of causal models. Social Science Research, 4, 113-133.
- SPSSX. (1986). User's guide. Chicago: SPSSX, Inc.
- Stage, F. K. (1989). An alternative to path analysis: A demonstration of LISREL using students' commitment to an institution. Journal of College Student Development, 30, 129-135.
- Sullivan, J. L. (1971). Multiple indicators and complex causal models, in H. M. Blalock (Ed.), Causal models in the social sciences, Chicago: Aldine.
- Sullivan, J. L. (1974). Multiple indicators: Some criteria of selection, in H. M. Blalock (Ed.), Measurement in the social sciences, Chicago: Aldine.
- Vance, V. S. & Schlechty, P. C. (1982). The distribution of academic ability in the teaching force: Policy implications. Phi Delta Kappan, 64(1), 22-27.
- Veeman, S. (1984). Perceived problems of beginning teachers. Review of Educational Research, 54(2), 143-178.
- Warren, R. D., Fear, F. A., & Klomglan, G. E. (1980). Social-indicator model building: A multiple-indicator design. Social Indicators Research, 7, 269-297.

- Warren, R. D. & Kemis, M. R. (1989). Multiple Indicators of Variables in a Longitudinal Study of Teacher Preparation and Teaching (Report No. 3 in the Project: Model Applications in Education). Ames, IA: Iowa State University.
- Warren, R. D., Klonglan, G. E., & Faisal, C. S. (1977). Causal model analysis. Sociology Report No. 135. Ames: Iowa State University, Department of Sociology and Anthropology.
- Warren, R. D., White, J. K., & Fuller, W. A. (1974). An errors-in-variables analysis of managerial role performance. Journal of the American Statistical Association, 69, 886-893.
- Weaver, W. T. (1979). Educators in supply and demand: Effects on quality. Paper presented at the meeting of the American Educational Research Association, New York, NY. (ERIC ED 143 145)
- Wiley, D. E. (1973). The identification problem for structural equation models with unmeasured variables. In A. S. Goldberg & O. D. Duncan (Eds.), Structural Equation Models in the Social Sciences. New York: Seminar Press.
- Williams, M. A. (1985). A prediction of student teaching satisfaction of the Iowa State teacher education graduates using a combination of selected variables. Unpublished doctoral dissertation, Iowa State University, Ames, IA.
- Winer, B. J. (1962). Statistical principles in experimental design. New York: McGraw-Hill.
- Wright, S. (1934). The method of path coefficients. Annals of Mathematical Statistics, 5, 161-215.
- Yarger, S. J., Howey, K., & Joyce, B. (1977). Reflections on preservice education: Impressions from the national survey. Journal of Teacher Education, 28(6), 34-36.

ACKNOWLEDGEMENTS

I would like to thank all those people who provided help and encouragement toward the completion of this dissertation.

To my committee members, Dr. Ann Thompson, Dr. Bill Miller, Dr. Bill Rudolph, and Dr. Mack Shelley, thank you. Your kindness, understanding, and cooperation were greatly appreciated.

Special appreciation is extended to Dr. Mary Huba and Dr. Richard Warren (major co-chairpersons) for their guidance and encouragement throughout this undertaking. I am especially grateful to Dr. Warren for his theoretical and technical assistance and constructive criticisms provided during my research endeavor.

My thanks also go to RISE staff members Mari Kemis and Alyce Holland. For the help and support I received, I am grateful.

My deepest appreciation is for my family and wife, Linda, whose support, encouragement, patience, and sacrifice made this possible.

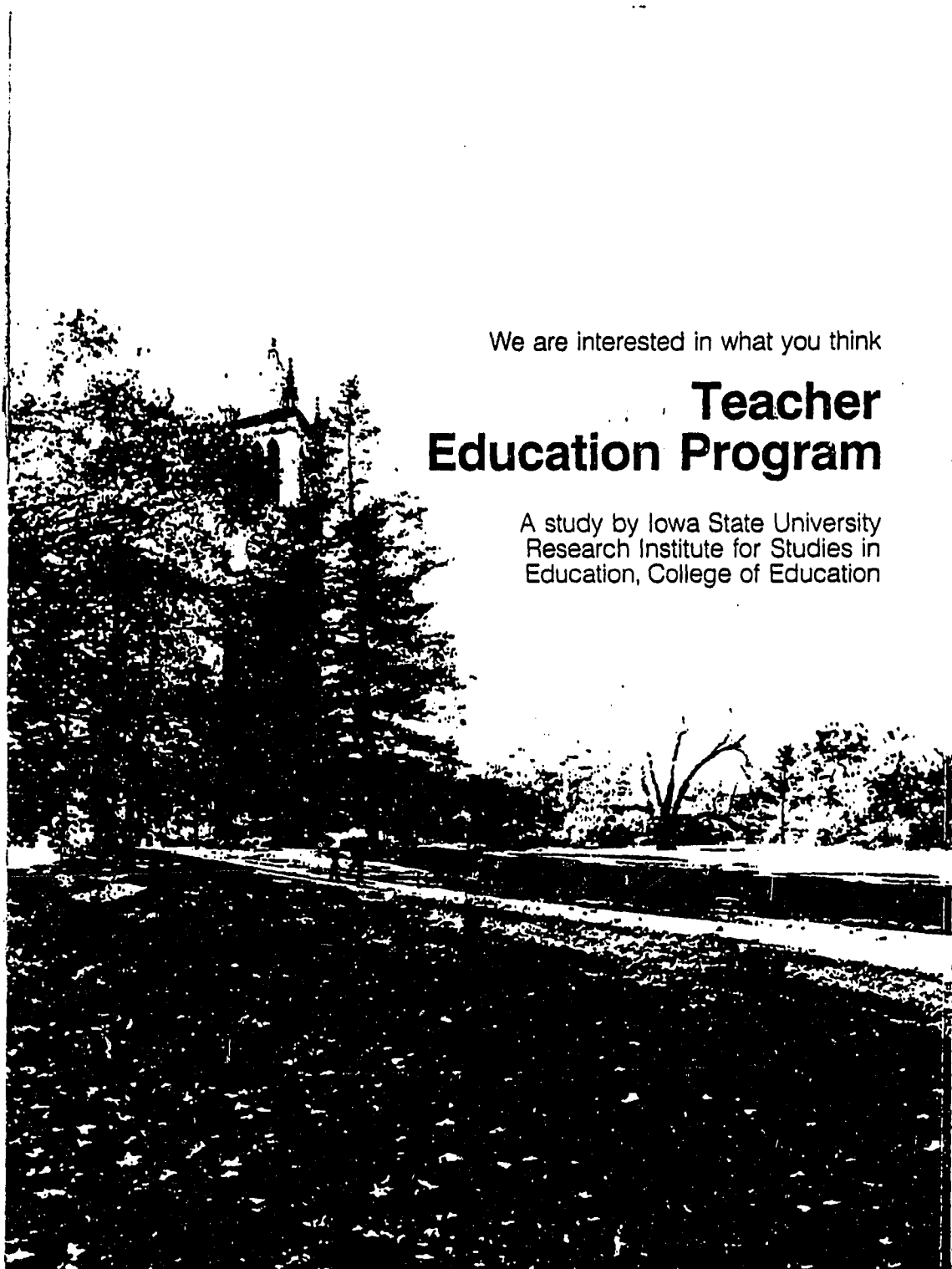
APPENDIX A

TEACHER EDUCATION PROGRAM SURVEY

We are interested in what you think

Teacher Education Program

A study by Iowa State University
Research Institute for Studies in
Education, College of Education



Spring 1988

A Note to Respondents

In recent years, the teaching profession has been marked by rapid change and the emergence of a number of issues and concerns. It is essential that teacher preparation programs be responsive to these concerns. Therefore, the ISU College of Education is developing a comprehensive model to evaluate and to improve the quality of the teacher preparation program. Your reactions to and responses about your preparation are a major ingredient of this model.

Various approaches are used by colleges of education to evaluate, improve, and modify programs for the preparation of educational personnel. Among these approaches in the evaluation process is a study of graduates from preparation programs. To provide the necessary information for program improvement, the data need to be collected on a regular basis and over a period of time. These longitudinal studies are beneficial in providing insights about program strengths and weaknesses and in assisting in program improvement and modification.

Since 1979, the Research Institute for Studies in Education (RISE) has been collecting data from teacher education graduates at major points in their preparation and careers. Now, at graduation, we are contacting you for information about your current attitudes towards the ISU Teacher Preparation Program and personal background characteristics. The information we receive is summarized and presented in a report that is discussed by faculty in the College of Education as they plan changes for improving and updating the teacher preparation program. As mentioned in the accompanying letter, no individual responses are ever reported.

These data, collected over the past eight years, have been very helpful in keeping the ISU Teacher Preparation Program current and responsive to changing educational needs. Your input is very much appreciated.

FIRST, we would like information about your teacher preparation program.

1. How long did you student teach? (check one)

8 weeks or less

12 weeks

16 weeks

Other (Please specify ---> _____).

2. Based on the length of your student teaching experience, should student teaching have been longer or shorter?

	How many additional weeks?	How many fewer weeks?	Total suggested weeks
<input type="checkbox"/> Longer --->	_____	xxxxxxxxxx	_____
<input type="checkbox"/> Shorter --->	xxxxxxxxxx	_____	_____
<input type="checkbox"/> About right	xxxxxxxxxx	xxxxxxxxxx	xxxxxxxxxx

3. At what level did you student teach?

Prekindergarten/Kindergarten (N-K)

Elementary (K-6)

Secondary (7-12)

K-12

4. In what teaching area(s) of specialization do you expect to get teaching approval?

(a) Prekindergarten/Kindergarten Level

Prekindergarten/Kindergarten Other (Specify _____)

(b) Elementary Level

Elementary Other (Specify _____)

(c) K-12 Level

Art Health Music P.E.

(d) Secondary Level

<input type="checkbox"/> Agriculture	<input type="checkbox"/> Health	<input type="checkbox"/> Physical Science
<input type="checkbox"/> Art	<input type="checkbox"/> Home Economics	<input type="checkbox"/> Physics
<input type="checkbox"/> Biology	<input type="checkbox"/> Industrial Arts	<input type="checkbox"/> Psychology
<input type="checkbox"/> Chemistry	<input type="checkbox"/> Journalism	<input type="checkbox"/> Safety Education
<input type="checkbox"/> Earth Science	<input type="checkbox"/> Mathematics	<input type="checkbox"/> Social Science
<input type="checkbox"/> English	<input type="checkbox"/> Music	<input type="checkbox"/> Speech
<input type="checkbox"/> Foreign Language	<input type="checkbox"/> Physical Education	<input type="checkbox"/> Other
<input type="checkbox"/> General Science		

If you checked more than one, what is your major area? _____

5. Using the rating scale below, indicate how satisfied you were with aspects of your student teaching experience.

- Very Satisfied 5
- Satisfied 4
- Neutral 3
- Dissatisfied 2
- Very Dissatisfied . . . 1

Please circle your response

- a. Getting your choice of geographical location for your student teaching assignment. 5 4 3 2 1
- b. Your cooperating teacher. 5 4 3 2 1
- c. Your university supervisor. 5 4 3 2 1
- d. Based on your student teaching experience, what is your reaction to teaching as a career for you? 5 4 3 2 1

6. At what age did you decide to become a teacher? _____ years old.

7. If you had it to do over again, would you prepare to become a teacher?

- Yes
- No
- Undecided

8. Do you feel you will be ...

- ... an excellent teacher?
- ... a better than average teacher?
- ... an average teacher?
- ... a below average teacher?
- ... an inadequate teacher?

9. On a scale of 0 to 10, how would you rate the quality of the Teacher Preparation Program at Iowa State University? (Please circle the appropriate number.)

Very Poor Very High

 0 1 2 3 4 5 6 7 8 9 10

10. In what ways did the program provide the most valuable professional preparation for you?

(1) _____
 (2) _____
 (3) _____

11. In what ways should the program have offered more preparation?

(1) _____
 (2) _____
 (3) _____

- 12a. During your academic program at Iowa State University, have you done any work with computers or had training with applications of computers to teaching?

___ No ----> go to Q. 13a
 ___ Yes ---> please answer Q. 12b

- 12b. If yes, please check all experiences that apply.

- ___ 1. Introductory lecture(s)/demonstration(s) on computers and educational applications
 ___ 2. Viewing available Computer Assisted Instruction (CAI) materials
 ___ 3. Selecting and evaluating Computer Assisted Instruction (CAI) materials
 ___ 4. Using computers to manage instruction (grades, attendance, etc.)
 ___ 5. Entire course(s) in educational computing or computer science
 ___ 6. Word processing
 ___ 7. Computer programming
 ___ 8. Using microcomputers (Apple, IBM PC, etc.)
 ___ 9. Using minicomputers (VAX)
 ___ 10. Using mainframe computers through terminal and batch processing
 ___ 11. Other (Please specify ---> _____).

13a. Please indicate how adequate your professional education preparation program was in the following areas. Use the following response categories.

Very Adequate . . . 5
 Adequate 4
 Neutral 3
 Inadequate 2
 Very Inadequate . . . 1
 Not Applicable . . . N

	Please circle your response					
1) Planning units of instruction and individual lessons	5	4	3	2	1	N
2) Preparing and using media	5	4	3	2	1	N
3) Maintaining student interest	5	4	3	2	1	N
4) Understanding and managing behavior problems in the classroom	5	4	3	2	1	N
5) Teaching basic skills	5	4	3	2	1	N
6) Consultation skills in interacting with other professionals	5	4	3	2	1	N
7) Developing student-student relationships	5	4	3	2	1	N
8) Referring students for special assistance	5	4	3	2	1	N
9) Skills for mainstreaming handicapped students	5	4	3	2	1	N
10) Methods of working with children with learning problems	5	4	3	2	1	N
11) Assessing learning problems	5	4	3	2	1	N
12) Developing tests	5	4	3	2	1	N
13) Interpreting and using standardized tests	5	4	3	2	1	N
14) Content preparation in your area of specialization	5	4	3	2	1	N
15) Professional ethics and legal obligations	5	4	3	2	1	N
16) Psychology of learning and its application to teaching	5	4	3	2	1	N
17) Evaluating and reporting student work and achievement	5	4	3	2	1	N
18) Relating activities to interests and abilities of students	5	4	3	2	1	N

Very Adequate . . . 5
 Adequate. 4
 Neutral 3
 Inadequate. 2
 Very Inadequate . . 1
 Not Applicable. . . N

Please circle your response

- 19) Locating and using materials and resources
 in your specialty area. 5 4 3 2 1 N
- 20) Evaluating your own instruction 5 4 3 2 1 N
- 21) Individualizing instruction 5 4 3 2 1 N
- 22) Selecting and organizing materials. 5 4 3 2 1 N
- 23) Using a variety of instructional techniques . . 5 4 3 2 1 N
- 24) Understanding teachers' roles in relation to
 administrators, supervisors and counselors. . . 5 4 3 2 1 N
- 25) Working with parents. 5 4 3 2 1 N
- 26) Working with other teachers 5 4 3 2 1 N
- 27) Assessing and implementing innovations. . . . 5 4 3 2 1 N
- 28) Appreciating and understanding
 individual and intergroup differences
 in values and lifestyles 5 4 3 2 1 N
- 29) Using community resources 5 4 3 2 1 N
- 30) Techniques of curriculum construction 5 4 3 2 1 N
- 31) Influence of laws and policies
 related to schools. 5 4 3 2 1 N
- 32) Techniques of infusing multicultural
 learning. 5 4 3 2 1 N
- 33) Using written communication effectively 5 4 3 2 1 N
- 34) Developing your own teaching style
 by observing others 5 4 3 2 1 N

13b. In rank order (1 highest rank), please list from the above items the corresponding numbers for the three areas of preparation with highest adequacy.

	1	2	3
Adequacy of Preparation	—	—	—

14. We would like your reactions to using selected components within the teacher preparation program. Some of these components are recent additions and therefore, may not have been included in your program. First, for each component, please check (✓) whether or not you participated. Then, for those you participated in, use the scale below to rate the extent to which the component helped you prepare to be a teacher. Finally, comment on the component (such as, explain what you liked or disliked, how it helped you, the extent of your participation, its strengths or weaknesses, etc.)

No Help at All A Great Deal of Help

 0 1 2 3 4 5 6 7 8 9 10

<u>Component</u>	<u>Participate</u>	<u>Rating</u>	<u>Comments</u>
Teachers on Television (TOT)	<input type="checkbox"/> Yes <input type="checkbox"/> No	<input type="text"/> <input type="text"/> <input type="text"/>	<input type="text"/> <input type="text"/> <input type="text"/>
Performance Element Modules (PEMs)	<input type="checkbox"/> Yes <input type="checkbox"/> No	<input type="text"/> <input type="text"/> <input type="text"/>	<input type="text"/> <input type="text"/> <input type="text"/>
Teaching Assessment Modules (TAMs)	<input type="checkbox"/> Yes <input type="checkbox"/> No	<input type="text"/> <input type="text"/> <input type="text"/>	<input type="text"/> <input type="text"/> <input type="text"/>
Writing Clinic	<input type="checkbox"/> Yes <input type="checkbox"/> No	<input type="text"/> <input type="text"/> <input type="text"/>	<input type="text"/> <input type="text"/> <input type="text"/>
Field Experiences (including pre-student teaching practicums, but not student teaching)	<input type="checkbox"/> Yes <input type="checkbox"/> No	<input type="text"/> <input type="text"/> <input type="text"/>	<input type="text"/> <input type="text"/> <input type="text"/>

15. What are your employment plans for the 1988/1989 school year?
- Have obtained a teaching position for 1988/89 school year.
 - Currently seeking or plan to seek a teaching position.
 - Currently seeking or plan to seek a non-teaching position.
 - Graduate study (Please specify area ---> _____).
 - Other (Please specify ---> _____).
16. What is your long-range career plan? (Please check the most appropriate response. Check only one.)
- Teaching ---> skip to Q. 18
 - Employment in education other than teaching ---> skip to Q. 18
Please specify ---> _____
 - Employment outside the field of education ---> please answer Q. 17
Please specify ---> _____
 - Other ---> please answer Q. 17
Please specify ---> _____
17. (Non-teaching) Why do you plan not to enter the field of education? Check as many as apply.
- Lack of teaching positions available.
 - Greater career opportunities in nonacademic jobs.
 - Higher salaries and benefits in nonacademic jobs.
 - Marriage/family obligations.
 - Had not planned to enter education.
 - Experiences in student teaching.
 - General working conditions (nonteaching duties, hours, classroom size, work load).
 - Student related (motivation, lack of discipline, general attitudes).
 - General administrative framework in local schools.
 - Lack of respect.
 - Emotional aspects (stress, burnout, frustration, boredom).
 - Lack of support from parents and community.
 - Lack of advancement opportunities.
 - Other (Please specify ---> _____).

ALL RESPONDENTS

18. How important is it that a job provide you with the following characteristics? Please circle one number for each characteristic. Use the following response categories.

Very Important . . . 5
 Important. 4
 Neutral. 3
 Unimportant. 2
 Very Unimportant . . 1

Please circle your response

a. Opportunity to be creative and original. . .	5	4	3	2	1
b. Opportunity to use special abilities or aptitudes.	5	4	3	2	1
c. Opportunity to work with people rather than things.	5	4	3	2	1
d. Opportunity to earn a good deal of money . .	5	4	3	2	1
e. Social status and prestige	5	4	3	2	1
f. Opportunity to effect social change.	5	4	3	2	1
g. Relative freedom from supervision by others.	5	4	3	2	1
h. Opportunity for advancement.	5	4	3	2	1
i. Opportunity to exercise leadership	5	4	3	2	1
j. Opportunity to help and serve others	5	4	3	2	1
k. Adventure.	5	4	3	2	1
l. Opportunity for a relatively stable and secure future.	5	4	3	2	1
m. Fringe benefits (health care, retirement benefits).	5	4	3	2	1
n. Variety in the work.	5	4	3	2	1
o. Responsibility	5	4	3	2	1
p. Control over what I do	5	4	3	2	1
q. Control over what others do.	5	4	3	2	1
r. Challenge.	5	4	3	2	1

19. In self-appraisal and teacher evaluation, certain teaching behaviors are often identified. We would like you to rate your perception of your student teaching behavior in each of the following areas. Using the scale below, circle a number for each area.

	Very Low	-----								Very High	
a. Providing a setting conducive to learning	0	1	2	3	4	5	6	7	8	9	10
b. Motivating students	0	1	2	3	4	5	6	7	8	9	10
c. Demonstrating knowledge of subject matter.	0	1	2	3	4	5	6	7	8	9	10
d. Monitoring and evaluating student progress and understanding.	0	1	2	3	4	5	6	7	8	9	10
e. Providing clear, concise explanations and examples.	0	1	2	3	4	5	6	7	8	9	10
f. Managing instructional activities efficiently and ensuring student time on task.	0	1	2	3	4	5	6	7	8	9	10
g. Communicating effectively with students.	0	1	2	3	4	5	6	7	8	9	10
h. Demonstrating sensitivity toward students.	0	1	2	3	4	5	6	7	8	9	10
i. Demonstrating effective planning and organization skills	0	1	2	3	4	5	6	7	8	9	10
j. Exhibiting a positive self-concept.	0	1	2	3	4	5	6	7	8	9	10
k. Accommodating a variety of ability levels.	0	1	2	3	4	5	6	7	8	9	10
l. Implementing the lesson plans effectively	0	1	2	3	4	5	6	7	8	9	10
m. Maintaining high expectations for student achievement	0	1	2	3	4	5	6	7	8	9	10
n. Incorporating effective questioning techniques.	0	1	2	3	4	5	6	7	8	9	10
o. Using a variety of instructional resources	0	1	2	3	4	5	6	7	8	9	10
p. Maintaining high standards for student behavior.	0	1	2	3	4	5	6	7	8	9	10

Now we would like to ask you some general questions about yourself and your family.

20. Up to the present, where have you spent the majority of your life?
- ... on a farm?
 - ... in a non-farm country home?
 - ... in a town with population less than 2,500?
 - ... in a town with population between 2,500 and 5,000?
 - ... in a town with population between 5,000 and 10,000?
 - ... in a town with population between 10,000 and 25,000?
 - ... in a town with population between 25,000 and 50,000?
 - ... in a city with population between 50,000 and 100,000?
 - ... in a city with population over 100,000?

21. Sex
- Female
 - Male

22. Marital status

Single
 Married

- 22a. Do you have any children?

Yes ---> How many? ____
 No

23. What was your father's occupation most of the time while you were living at home? Please be specific.

24. What was your mother's occupation most of the time while you were living at home? Please be specific.

25. Please think about the best elementary or secondary teacher you know or have known. What are the characteristics that made that teacher outstanding?

(1) _____

(2) _____

(3) _____

If you have any additional comments about teacher preparation or teaching in general, please use the space below.

The College of Education and the Research Institute for Studies in Education appreciate the time you have taken to complete this questionnaire. Postage for the questionnaire is prepaid, so all you need to do is tape it and drop it in a mailbox.

APPENDIX B

SUGGESTED STEPS FOR STRUCTURAL EQUATION MODEL ANALYSIS

Suggested steps for structural equation model analysis:

1. Formulation of a model
 - 1.1 Identify relevant variables
 - 1.2 Determine causal ordering
2. Measurement conditions determine method of analysis
 - 2.1 Single indicator - no measurement error
 - 2.1.1 Multiple linear regression
 - 2.1.2 LISREL
 - 2.2 Single indicator - adjust for measurement error
 - 2.2.1 LISREL
 - 2.3 Multiple indicators - with or without measurement error
 - 2.3.1 LISREL
3. Identification of model
 - 3.1 If method is multiple regression, model is identified
 - 3.2 If method is LISREL, identification may be a problem
 - 3.2.1 Use identification procedures discussed
 - 3.2.2 Use LISREL to determine identification
 - 3.2.2.1 Parameter matrix should be positive definite
 - 3.2.2.2 All variances should be positive
 - 3.2.2.3 Standardized solutions should be in the range from -1 to 1
4. Estimate parameters
 - 4.1 Path coefficients
 - 4.2 Residuals
5. Interpret results
 - 5.1 Multiple regression
 - 5.1.1 R square for explained variance
 - 5.1.2 Reduced model
 - 5.1.3 Test model if model is overidentified (Specht's test)
 - 5.2 LISREL
 - 5.2.1 Test model if model is overidentified
 - 5.2.1.1 Chi-square
 - 5.2.1.2 Goodness of fit index

5.2.1.3 Adjusted goodness of fit index

5.2.1.4 Root mean square residual

5.3 Relate results back to theory