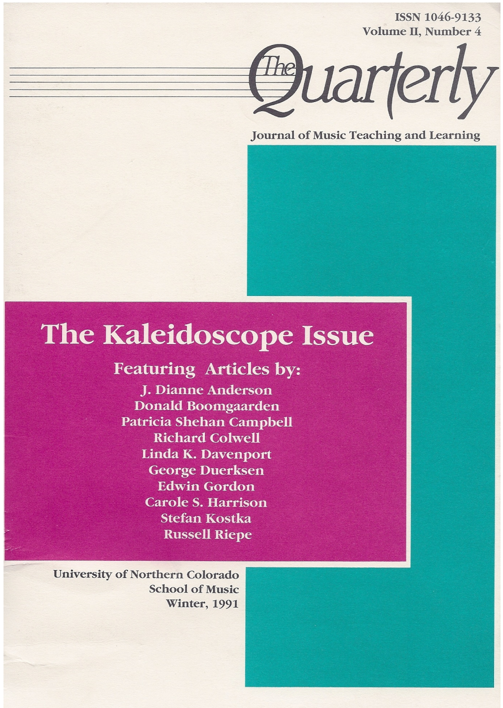

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Analyses Of Relationships Between Aural Skills And Background Variables: LISREL Versus Multiple Regression

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The fundamental task of research in music education, as in other disciplines, is to explain phenomena. The phenomena and constructs of music—musical aptitude, aural skills, perception of pitch and rhythm, motivation, achievement, performing skills—are especially complex in that they have many facets and causes, or in research terms, many sources of variation. Studying these phenomena and constructs in a research setting involves identification of the sources of variation. Many techniques that analyze variability between and among variables are available. It is important, however, that we realize the restrictions we impose on our investigations by the techniques(s) we choose, since the techniques not only set limits to the scope and nature of the answers we obtain from data, but also affect the type of questions we ask and the manner in which the questions are formulated. Furthermore, statistical techniques *per se* mean little unless they are integrated within a theoretical context and applied to data obtained in an appropriately designed study.

The primary purpose of this article is to provide an overview of linear structural equation modeling, one of the newer approaches to the study of variability and causation among variables. Using a simple model and the LISREL computer program, I show how the technique can be used to translate a verbal theory into a mathematical model that can be estimated and tested, and from which inferences can be drawn. To highlight the advantages of linear structural equation modeling, the technique is compared to multiple regression analysis, the technique traditionally used in predictive studies. The same data are analyzed by both techniques, and the results of the analyses are compared. Path diagrams are provided for both approaches in order to facilitate the comparison.

The Data

The data used in this study (N = 160) are from a series of investigations I have been conducting on the relationships between achievement in first semester music theory coursework and measures of musical aptitude, academic ability, and background experience in music. The variables selected for use as independent variables include those which were found to be the best predictors of grades in the ear-training and sight-singing components of the first-semester music theory course, as determined by multiple regression analyses (Harrison, 1990). The variables indicating grades in the ear-training and sight-singing compo-

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nents of the theory course serve as the dependent variables.

Regression Analysis

Regression analyses of various types, including multiple, hierarchical, and stepwise, allow one to assess the relationship between one dependent variable and several independent variables as the result of finding a best-fit line (minimum rms error) determined by the values of the dependent and independent variables. The general problem for regression is to arrive at the set of regression coefficients (b values), or standardized regression coefficients (β), for the independent variables that bring the values of the dependent variable predicted from the equation as close as possible to the values of the dependent variable obtained from measurement. One of the important statistics derived from the regression analysis is the multiple correlation coefficient (R) that is a correlation coefficient between the actual and predicated values of the dependent variable. The square of the multiple correlation coefficient (R^2) indicates the amount of variation in the dependent variable that is accounted for by the independent variables.

Using the modeling conventions of LISREL, figures 1 and 2 show the researcher's hypothesis regarding the process by which the six independent variables used in this study predict each of the dependent variables in the completed regression analyses. In LISREL path diagrams, circles are used to indicate concepts or latent variables which cannot be directly measured (e.g., tonal ability), and squares are used to indicate the measures of these latent variables (e.g., scores on the Tonal Imagery test of CMAP) (Schleuter, 1978; Schleuter & Schleuter, 1978). The LISREL symbolism used in Figures 1 and 2 also illustrates the assumptions that underlie the regression analyses. Note that each concept has only one indicator, implying that the single measure fully captures the concept. And each indicator is treated as being a perfectly reliable and valid measure of the con-

Table 1. The Variables Used in This Study

Abbreviation	Description
Independent Variables:	
CMAPton1	Scores on the Tonal Imagery test (40 items) of the experimental college version of the Musical Aptitude Profile (CMAP) (Schleuter, 1978; Schleuter & Schleuter, 1978). The CMAP tests were taken prior to the first semester of music theory coursework.
CMAPrhy	Scores on the Rhythm Imagery test (40 items).
Hsgpa	High school grade point averages as provided by Admissions and Records.
SATvrbl	Scores on the verbal component of the Scholastic Aptitude Test (SAT) as provided by Admissions and Records.
SATmath	Scores on the math component of the SAT.
Yrsmuexp	Total number of years of experience on all instruments, as derived from the questionnaire.
Dependent Variables:	
Eartraing	Grades in the ear-training component of the first-semester music theory course. A scale of 3 to 16 points was used (F = 3; A+ = 16). Grades for all assignments and tests were based on the number of errors made.
LSightsng	A logarithmic transformation of the variable indicating grades in the sight-singing component of the theory course. A scale of 3 to 6 points was used (F = 3; A+ = 16). Grades for all assignments and tests were based on the number of errors made. Fluency of performance within the context of tempo was also a consideration.

cept it presumably measures. Thus the indicators have reliability/validity coefficients of 1.00 and zero errors associated with them.

Needless to say, the assumption that variables such as those used in this study can be measured without error is unrealistic. Certainly the grading practices of individual instructors vary, and these variations are reflected in the grades for individual courses or components of courses (e.g., ear-training), as well as in overall high school grade point averages. Furthermore, it is well known that there is no test that is perfectly reliable. And while some of the errors are random, many sources of error are not and hence affect the validity of the measure. Systematic errors in measurement of a dependent variable and/or the independent variables lead to a downward bias in the estimation of the standardized regression coefficients as well as in R^2.

Another problem one encounters when doing multiple regression analysis is multicollinearity, that is, the variables are correlated rather than linearly independent. They really measure the same thing, and thus they vary together. Multicollinearity is often inadvertently introduced in studies by the use of multiple indicators for variables in which the researcher has great interest or considers important from a theoretical point of view. While multiple regression analysis accommodates correlated independent variables, high multicollinearity leads to imprecise estimation of regression coefficients and affects the standard errors of the regression coefficients. When there are only two independent variables, the presence and degree of multicollinearity is immediately apparent; it is the correlation between them. When there are more than two independent variables, however, it is far more difficult to identify the degree and source of the dependency, and popular computer programs are not designed to isolate it. Consequently, when multicollinearity is relatively high, the researcher is forced to conclude that most or all the variables have little direct effect on the dependent variable, and that the correlations are largely due to correlated causes that cannot be analyzed (Pedhazur, 1982).

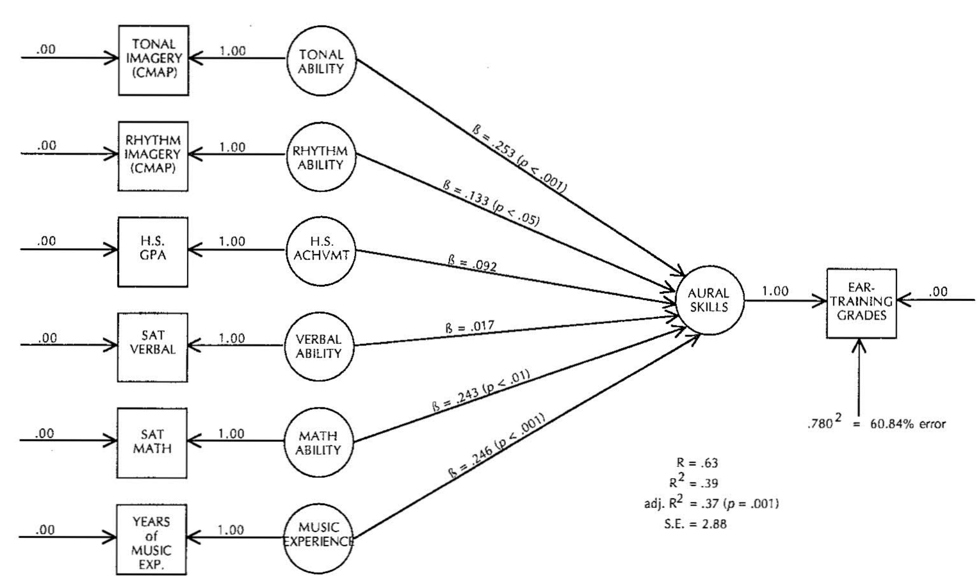


Figure 1. Prediction of Grades in Ear-Training (Multiple Regression Analysis)

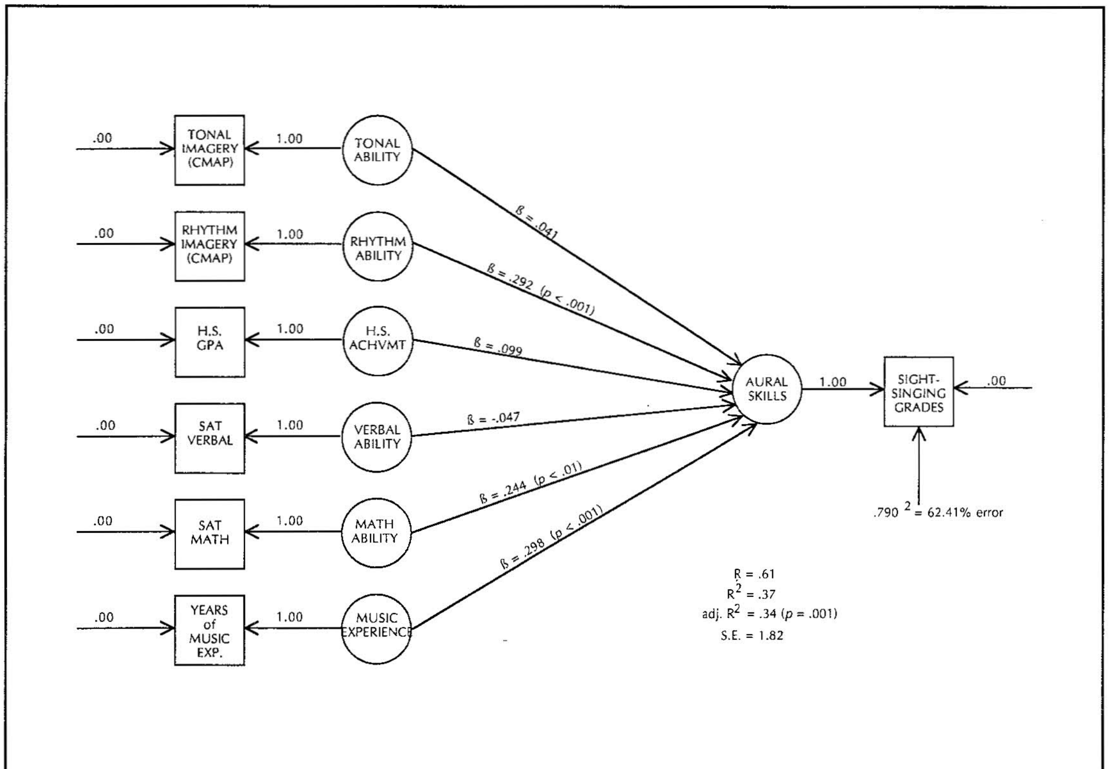


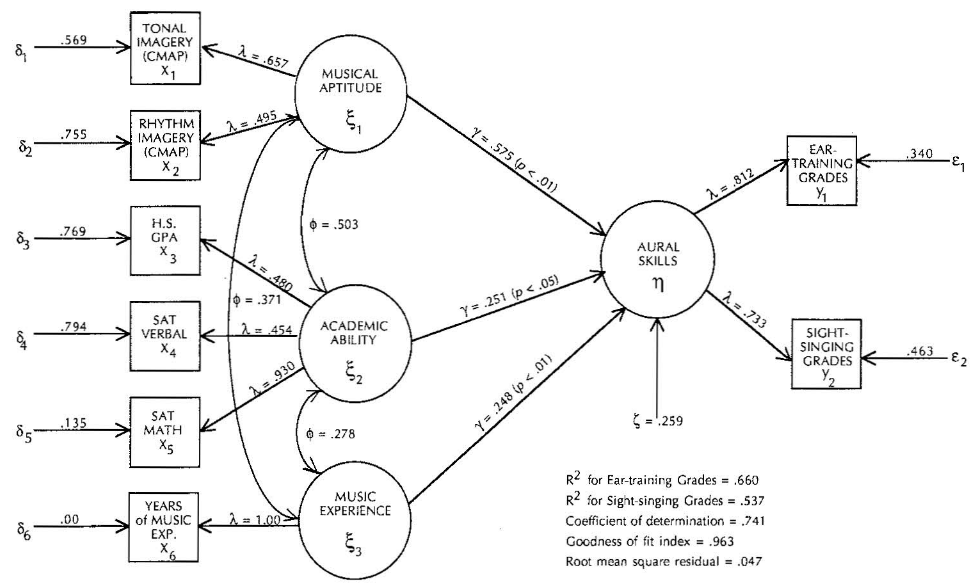
Figure 2. Prediction of Grades in Sight-Singing (Multiple Regression Analysis)

Probably the greatest difficulty one has when doing regression analysis is correct interpretation of the multiple correlation coefficient. While a high multiple correlation indicates a lot of shared variability, it does not indicate that the variables are causally related. Shared variability can result from other sources including the influence of variables not included in the equation. And, as Pedhazur (1982) points out, variables used in nonexperimental research may be, and often are, proxies for causal variables that are not included in the regression equation. For example, total years of performing experience could be a proxy for motivation and/or parental influence. No matter how large the regression coefficient associated with a variable, any interpretation of it is meaningless if the variable is serving as a proxy for a variable not included in the study.

Thus, while multiple regression analyses are powerful techniques, they do not factor our measurement errors in the variables, and they do not provide the information needed to readily identify multicollinearity and other problems discussed above. Recently, however, techniques which do address these concerns and which are designed to analyze posited causal relations among variables have been developed. The generic term used for the various approaches is structural equation modeling. And it is the (linear) structural equation model and the LISREL computer program that are the focus of this paper.

Linear Structural Equation Modeling and LISREL

Linear structural equation models are used to analyze proposed causal relationships among variables in nonexperimental and quasi-experimental research. Probably the most popular approach to linear structural equation modeling is represented by the computer program LISREL (linear structural relations) (Jöreskog, 1973). And while LISREL is a computer program, it has played such a vital role in the acceptance and application of linear modeling that models are often referred to as "LISREL models" (Long, 1983). Therefore, in order to avoid confusion, I will use "LISREL" when referring to



All coefficients are from the standardized solution except the errors in measurement for the observed variables.

Figure 3. The Effects of Musical Aptitude, Academic Ability, and Music Experience on Aural Skills (Structural Equation Model)

the computer program and "linear structural equation modeling" when discussing the modeling process.

LISREL is versatile and provides for a variety of models. It can be used to analyze data from surveys, experiments, quasi-experimental designs, and longitudinal studies. LISREL allows one to test the goodness of fit of models, to diagnose problems with models, and to make modifications (based on theory), to fix or constrain model coefficients, to do multiple-group analyses, and to distinguish between latent concepts and observed indicators (Hayduk, 1987). It also provides for measurement error, correlation of errors, simultaneous causation, and the omission of important explanatory variables, thereby providing much information that regression analysis does not.

LISREL consists of two major components: (1) the structural equation model and (2) the measurement model. Each component will be briefly discussed in relation to the data and analysis used in this study.

The construction of the structural model begins with the researcher's statement of a verbal theory that indicates the hypothesized relations among a set of variables. Often these variables are constructs or concepts, e.g., musical aptitude, academic ability, aural skills, and therefore unobserved. Such variables are referred to as latent variables. In LISREL, latent dependent, or endogenous, variables are designated as η (eta), whereas latent, independent, or exogenous, variables are designated as ξ (xi). In the path diagram, which is a visual representation of the hypothesized theory, latent variables are represented by circles.

As can be seen in Figure 3, this study involves one latent dependent (endogenous) variable, Aural Skills, and three latent independent (exogenous) variables, Musical Aptitude, Academic Ability, and Music Experience. The structural model attempts to account for variation and covariation in the latent endogenous variable(s) by specifying their causal dependence on the exogenous variables or on other endogenous variables. As indicated in Figure 3, I hypothesized that the latent dependent variable Aural Skills is affected by Musical Aptitude, Academic Ability, and Music Experience. The coefficients that indicate the direct effects of Musical Aptitude, Academic Ability, and Music Experience on aural skills are denoted as γ (gamma). The coefficients express the endogenous variables as linear combinations of the other variables. When the coefficients are taken from the standardized solution, as in this study, they can be interpreted as are the β (beta) coefficients in multiple regression analysis. It is assumed that variation in the latent exogenous variables is caused by variables outside of the model and not by the latent endogenous variables(s). In other words, Aural Skills does not affect Musical Aptitude or the other variables.

In this study, the latent exogenous variables, Musical Aptitude, Academic Ability, and Music Experience, were permitted to correlate. This is indicated by the curved lines linking them. The degree of correlation is indicated by the coefficient ϕ (phi). A residual or disturbance that represents all factors not included in the model, but which affect the latent endogenous variable, Aural Skills, is labeled ζ (zeta). While not included in the model analyzed in this study, LISREL also provides for the estimation of the effects of latent endogenous variables on other latent endogenous variables. For example, it could have been hypothesized that Music Experience not only affects Aural Skills, but is affected by Musical Aptitude and Academic Ability, in which case Music Experience would become a latent endogenous variable. The basic equation that encapsulates the postulated direct effects among the latent endogenous and exogenous variables is:

$$\eta = B\eta + \Gamma\xi + \zeta$$

The measurement component consists of a pair of confirmatory factor analysis models. The purpose of each model is to partition the variance of the indicators into variance originating in the underlying concept and variance due to error, thereby permitting one to study the meaningful relationships between the latent variables. One of these models links the exogenous variables, in circles, and their observed indicators, in squares, and the other links the endogenous variables and their observed indicators. As can be seen in Figure 3, the observed indicators of the exogenous variable, Musical Aptitude, are CMAP Tonal Imagery and Rhythm Imagery test scores, and the indicators of the exogenous variable, Academic Ability, are high school grade point averages, SAT verbal test scores, and SAT math test scores.

For the endogenous variable, Aural Skills, the observed indicators are grades in ear-training and grades in sight-singing. Since the values of the observed indicator variables are thought to arise from the underlying constructs, they are expressed as linear combinations of the latent variables. This relationship is shown in Figure 3 by the arrows from the latent variables to their indicators. The coefficient or loading which relates the indicator to the latent variable is λ (lambda). The reliability of the observed variable is defined as the squared correlation between the latent variable and its observed indicator, which is the square of the loading in this solution. As such, it indicates the percentage of variation in an observed variable that is explained by the construct or concept it is intended to measure (Long, 1983).

The proportions of variance in the indicators that are due to error in measurement are indicated by δ (delta) for the observed independent variables, and by ε (epsilon) for the observed dependent variables. In the path diagram, the error values are given above the arrows pointing to the indicators from outside the model. Since the latent variable, Music Experience, has only one indicator, Years of Music Experience, the loading of the latter on the former is 1.00 and the error variance is zero. This, of course, means that the indicator, Years of Music Experience, is being treated as a perfectly reliable and valid measure of Music Experience. It should be noted that I could have specified a value for the error variance of the indicator. Hayduk (1987) suggests that one determine the value of the error variance by multiplying the variance of the indicator by the proportion of the indicator that the researcher believes is error variance.

In summary, each of the factor analytic models for the measurement component of the model includes a matrix of the loadings of the observed indicator variables on the latent variables which are indicated by λ (lambda) and a vector of unique factors or errors in measurement, δ (delta) or ε (epsilon), that affect the indicator variables. The two equations that describe the measurement model are:

$$X = \Lambda_x \xi + \delta$$

$$y = \Lambda_y \eta + \varepsilon$$

Estimation

The objective of the estimation process is to obtain estimates of the model-implied variances and covariances (recorded by LISREL in matrix Σ) of the observed variables that come as close as possible to the variances and covariances of the observed variables provided by the data (recorded by the researcher in matrix S). When maximum likelihood estimation is used, as in this study, one can claim that the estimates maximize the likelihood of S arising as a sampling fluctuation around Σ. Comparison of the model's prediction (Σ) with observed reality (S) provides the basis for testing a model's adequacy and for obtaining reasonable estimates of the model's coefficients.

Assessing Goodness of Fit

There are a number of ways of assessing the adequacy of the estimated (hypothesized) model including examination of residuals, correlations among the estimates for (detection of multicollinearity), the significance of the estimates, modification indices, standard errors, squared multiple correlations, and coefficients of determination. If any of these quantities has an unreasonable value, it is an indication that the model is fundamentally wrong and not suitable for the data. Examples of such unreasonable values in the parameter estimates are correlations larger than one, negative variances, squared multiple correlations or coefficients of determination that are negative, and standard errors that are extremely large (Jöreskog & Sörbom, 1986).

LISREL gives squared multiple correlations for each observed variable separately, and for each structural equation. It also gives a coefficient of determination for all the observed variables jointly. The squared multiple correlation is a measure of the strength of the relationship, and the coefficient of determination is a measure of the strength of several relationships jointly, i.e., the percentage of the variation in the endogenous variable(s) that is explained by the model.

LISREL also provides three measures of overall fit. One is the overall χ^2 measure which tests the hypothesis that the observed covariance matrix was generated by the hypothesized model. Rejecting the hypothesis indicates that the model does not adequately reproduce the observed covariance matrix S. However, the measure is valid only if all the observed variables have a multivariate normal distribution, the analysis is based on the sample covariance matrix, and the sample size is fairly large. All three of these assumptions, of course, are seldom fulfilled in practice. To address these issues, LISREL provides two other measures of overall fit that are based on a comparison of the observed and predicted variances and covariances of the observed variables. One of these, the goodness-of-fit index is a measure of the relative amount of variances and covariances jointly accounted for by the model. Values generally range from zero to one. Unlike χ^2, the goodness-of-fit index is independent of the sample size and relatively robust against departures from normality. The other measure, the root mean square residual, is a measure of the residual variances and covariances when the observed and predicted covariance matrices are compared.

Method

The data used in this study were analyzed with the REGRESSION program of SPSS/PC+ (Norusis, 1986) and LISREL VI (Jöreskog & Sörbom, 1986). Internal consistency reliability coefficients (coefficient alpha) for the two CMAP tests used in the study (N=208) are: Tonal Imagery, .81; and Rhythm imagery, .71 (Harrison, 1990). For the regression analyses, alpha was relaxed (alpha = .85) so as to permit all six independent variables to enter the equation. Before the LISREL analysis was performed using the correlation matrix given in Table 2, all coefficients or parameters of the structural model were proven identified, i.e., the number of equations was determined to be equal to or more than the number of parameters to be estimated, thereby providing a unique solution for each parameter. (See references for discussion of identification.) In order to insure that the latent variables (Musical Aptitude, Academic Ability, Music Experience, and Aural Skills) were measured on the same measurement scale as the corresponding observed indicators, one loading (λ) was fixed to 1.00 for each concept.

Scatterplots and normal probability plots of residuals were examined to determine if the assumptions of normality, linearity, and homoscedasticity required for both regression analysis and LISREL were met. Because the assumptions were not met for the prediction of sight-singing grades, the distributions of the individual variables were examined. The variable indicating grades in the sight-singing component of the theory course was found to be severely skewed. A logarithmic transformation of the variable was performed and used in all analyses.

Results

Regression Analyses. For grades in the ear-training component of the course, the amount of variation accounted for is 39 percent ($p < .001$), with standardized regression coefficients ranging from .017 (alpha = .82) for the variable indicating scores on the verbal component of the SAT to .253 (alpha = .001) for the Tonal Imagery test. The four variables that predict grades in ear-training at a statistically significant level are: SAT math test scores, CMAP Tonal Imagery test scores, Years of Music Experience, and CMAP Rhythm Imagery test scores.

For grades in the sight-singing component of the first-semester music theory course, the total amount of variation accounted for by the independent or predictor variables is 37 percent ($p < .001$). Standardized regression coefficients indicating the relative importance of the predictor variables range from .041 (alpha = .58) for the Tonal Imagery test of CMAP to .298 (alpha = .001) for Years of Music Experience. As is indicated in Table 3, only three of the six variables are statistically significant predictors of grades in sight-singing: Years of Music Experience, CMAP Rhythm Imagery test scores, and SAT math test scores.

LISREL Analysis. As indicated by the coefficient of determination for the structural equations, the total amount of variation accounted for in the model is 74 percent. The goodness-of-fit index is .963, indicating that the model fits the data well. The amounts of variation accounted for in ear-training and sight-singing grades, respectively, are 66 percent and 54 percent. The coefficients indicating the effects of Musical Aptitude, Academic Ability, and Music Experience on Aural Skills

Table 2. Correlations, Means, and Standard Deviations (N = 160)

VARIABLES	Eartraing	LSightsng	CMAPtonl	CMAPrhy	Hsgpa	SATvrbl	SATmath	Yrsmuexp
Eartraing	1.000	.595	.456	.293	.246	.247	.467	.408
LSightsng	.595	1.000	.296	.390	.228	.157	.404	.425
CMAPtonl	.456	.296	1.000	.325	.060	.212	.369	.248
CMAPrhy	.293	.390	.325	1.000	-.021	.037	.149	.176
Hsgpa	.246	.228	.060	-.021	1.000	.247	.447	.116
SATvrbl	.247	.157	.212	.037	.247	1.000	.419	.191
SATmath	.467	.404	.369	.149	.447	.419	1.000	.255
Yrsmuexp	.408	.425	.248	.176	.116	.191	.255	1.000
Means	9.20	9.94	30.20	35.00	3.19	444	490	8.94
S.D.	3.64	2.24	5.29	3.75	.446	106	104	4.16

Table 3. Results of Stepwise Regression Analyses for the Prediction of Grades in the Ear-Training and Sight-Singing Components of the First Semester Music Theory Course from Aptitude, Achievement, and Music Experience (N = 160)

VARIABLES	*r*	*R*	R^2	R^2 Change	*F* Change	*p* <	*b*	*Beta*
Criterion Measure = Ear-training								
SATmath	.467	.467	.218	.218	44.00	.001	.008	.243[b]
CMAPtonl	.456	.558	.311	.093	21.24	.001	.174	.253[a]
Yrsmuexp	.408	.611	.374	.063	15.66	.001	.215	.246[a]
CMAPrhy	.293	.623	.388	.014	3.55	.061	.129	.133[c]
Hsgpa	.246	.628	.395	.007	1.73	.190	.750	.092
SATvrbl	.247	.628	.395	.000	.06	.813	.001	.017
						Intercept = -9.278		
	Adjusted R^2 = .371*					S.E. = 2.884		
Criterion Measure = LSight-singing								
Yrsmuexp	.425	.425	.180	.180	34.80	.001	.161	.298a
CMAPrhy	.390	.532	.283	.103	22.47	.001	.174	.292a
SATmath	.404	.598	.357	.074	17.99	.001	.005	.244b
Hsgpa	.228	.603	.364	.007	1.63	.205	.005	.099
SATvrbl	.157	.605	.366	.002	.38	.541	-.001	-.047
CMAPtonl	.296	.606	.367	.001	.31	.576	.018	.041
						Intercept = -1.851		
	Adjusted R^2 = .342*					S. E. - 1.820		

* = .001 level of significance
Note: *R* and R^2 are incremental. Regression coefficients (*b*) and standardized regression coefficients (*Beta*) are from the final step of the analysis. [a] indicates significance at .001 level; [b] at .01 level; and [c] at .05 level.

are .575, .251, and .248 respectively (see Table 4 and Figure 3). The effects of all three are statistically significant. All normalized (standardized) residuals, which are estimates of the number of standard deviations the observed residuals are away from the zero residuals that would be provided by a perfectly fitting model, were less than 2, indicating that most or all of the error is random. As indicated by the ϕ (phi) coefficients, correlations between the latent exogenous variables are .503 (between Musical Aptitude and Academic Ability), .371 (between Musical Aptitude and Music Experience), and .278 (between Academic Ability and Music Experience). The correlations between the observed variables are uniformly smaller since their correlations are affected by errors in measurement (see Table 2).

Discussion and Conclusions

The results of both the regression analyses and the LISREL analysis indicate that achievement in the sight-singing and ear-training components relate to the measures of musical aptitude, academic ability, and music experience used in this study. However, the amount of variation in sight-singing and ear-training grades accounted for by each of the two techniques is substantially different. For the regression analyses, only 39 percent and 37 percent of the variation in ear-training and sight-singing grades, respectively, was accounted for by the indicators of Musical Aptitude, Academic Ability, and Music Experience. But in the LISREL analysis, error in the measurement of the variables was separated out, and 66 percent and 54 percent of the variation in grades was accounted for. Also, the effect coefficient for Musical Aptitude (.575) indicates a substantially stronger relationship between Musical Aptitude and Aural Skills than is evidenced in the results of the regression analyses. The provision for separation or partitioning of error variance from the variance of the indicator or latent variable is one of the major virtues of LISREL.

Further, because of the partitioning of variance one can readily identify the reliable and valid indicators of concepts by looking at the loadings and the error terms. Variables with

Table 4. Results of LISREL Analysis of Causal Model Hypothesizing Relationships Between Aural Skills and Musical Aptitude, Academic Ability, and Music Experience

Parameter	Effect	$p <$
Structural Coefficients:		
Effect of Musical Aptitude on Aural Skills	.575	.01
Effect of Academic Ability on Aural Skills	.251	.05
Effect of Music Experience on Aural Skills	.248	.01
Correlation Between Exogenous Variables:		
Musical Aptitude & Academic Ability	.503	.001
Musical Aptitude & Music Experience	.371	.001
Academic Ability & Music Experience	.278	.01
Measurement Model		
Loadings on the Exogenous Variables:		
CMAPtonl on Musical Aptitude	.657*	—
CMAPrhy on Musical Aptitude	.495	.001
Hsgpa on Academic Ability	.480*	—
SATvrbl on Academic Ability	.454	.001
SATmath on Academic Ability	.930	.001
Yrsmuexp on Music Experience	1.000*	—
Loadings on the Endogenous Variables:		
Eartraing on Aural Skills	.812*	—
LSightsng on Aural Skills	.733	.001
Reliabilities:		
CMAPtonl	.432	
CMAPrhy	.245	
Hsgpa	.230	
SATvrbl	.206	
SATmath	.865	
Yrsmuexp	1.000	
Eartraing	.659	
Sightsng	.537	
Goodness of fit:		
Coefficient of determination	.741	
Chi-square (*df*)	24.910 (15)	
Goodness of fit index	.963	
Root mean square residual	.047	

* Asterisk denotes a fixed parameter.

low loadings and high error coefficients can be replaced by indicators that more reliably measure the concept. Inspection of the loadings and error terms of the observed variables used in this study indicate that the more reliable measure of the latent variable Musical Aptitude is the Tonal Imagery test (λ = .657; reliability = .432), and that the most reliable measure of Academic Ability is the SAT math test (λ = .930; reliability = .865). Interestingly, both indicators of the latent variable, Aural Skills, have relatively high loadings (.812 for ear-training grades; .733 for sight-reading grades) and low error terms. This is surprising since grading in skill areas such as sight-singing and ear-training involves a certain amount of subjectivity. And, when subjective judgment is involved, one usually finds unreliability and a fairly large amount of error.

In addition, since the LISREL analysis is based on a model which hypothesized that Musical Aptitude, Academic Ability and Music Experience affect achievement in the aural skills components of the music theory course, and since the analysis indicates the fit of the model to the data is good and the coefficients indicating the effects are significant, one can infer that the three latent variables do affect achievement in aural skills. One can also infer that Musical Aptitude, with an effect coefficient of .575, has the greatest effect on achievement.

Summary

The underlying purpose of this paper is to demonstrate the importance of selecting the analytic technique that best answers the research question(s) being asked. We have reviewed the assumptions and limitations of multiple regression analyses and briefly discussed linear structural equation modeling and its advantages. Data from an ongoing study were analyzed by both LISREL and multiple regression techniques and the results compared. We have seen that while the results of the analyses by both techniques indicate significant relationships between achievement in the aural skills components of the music theory course and measures of musical aptitude, academic ability and music experience, the amount of variation accounted for is substantially different as is the strength of the relationships between variables.

As stated earlier, if the purpose of a study is to identify the independent variables that best predict a dependent variable, multiple regression techniques may be sufficient. If, however, the purpose of the study is to identify and "explain" the variation between complex concepts such as musical aptitude, academic ability, and aural skills, then linear structural equation modeling and LISREL should be used since it 1) permits the variables in the equation to be either directly observed variables or complex latent variables, 2) provides for separating out measurement error so that one can study the meaningful relationships between complex latent variables, and 3) provides more information needed for assessment of the adequacy of the hypothesized model and for identification of such problems as multicollinearity and the omission of important explanatory variables. And since "explanation" is a primary goal of most research and the key to creating requisite conditions for achievement of specific objectives, these are important considerations.

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