Path Analysis: An Introduction and Analysis of a Decade of Research

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ABSTRACT The authors review the use and interpretations of path analyses in articles published in *The Journal of Educational Research* from 1992 to 2002 and discuss related issues. This article provides (a) a brief introduction to path analysis, (b) suggested guidelines and recommendations for reporting results, (c) a sample of a model path analysis, (d) evaluation of the JER path analysis articles, and (e) concluding remarks.

Key words: path analysis, reporting research results, research methods

Several statistical techniques have been developed to help social scientists deal with studies that involve the analysis of hypothesized relationships among multiple variables. One technique, path analysis, is a variation of multiple-regression analysis and is useful for analyzing a number of issues involved in causal analysis. Path analysis, first developed in the 1920s, is a method for examining causal patterns among a set of variables. Researchers use path analysis most frequently to analyze data relative to a prespecified causal model. With path analysis, researchers conduct a series of regressions to analyze influences on dependent variables within the model. Frequently, dependent variables serve as independent variables for later regressions within the model. In some models, but not all, there is one ultimate dependent variable of interest to the researcher. A regression is conducted for each dependent variable and effects are calculated across regressions for cumulative effects.

Our purpose in this article is to review the use and interpretations of path analyses in articles published in *The Journal of Educational Research* from 1992 to 2002 and to discuss related issues. In the remainder of this article, we provide: (a) a brief introduction to path analysis, (b) suggested guidelines and recommendations for reporting results, (c) evaluation of the six path analysis articles that appeared in *The Journal of Educational Research* from 1992–2002, (d) a sample analysis of a model, and (e) a conclusion.

Path Analysis

Path analysis consists of a family of models that depicts the influence of a set of variables on one another (Spaeth, 1975). Path analysis is considered closely related to multiple regression. In fact, it is an extension of the regression model, which researchers use to test the fit of a correlation matrix with a causal model that they test (Garson, 2004). The aim of path analysis is to provide estimates of the magnitude and significance of hypothesized causal connections among sets of variables displayed through the use of path diagrams.

A *path diagram* is an illustration wherein the variables are identified and arrows from variables are drawn to other variables to indicate theoretically based causal relationships. A single-headed arrow points from cause to effect. A double-headed, curved arrow indicates that variables are merely correlated; no causal relations are assumed. The independent (X) variables are called exogenous variables. The dependent (Y) variables are called endogenous variables.

Figure 1 (Baron & Kenny, 1986) illustrates several different types of structures that express possible causal relationships underlying a covariation. In (a), Z is not connected causally to either X or Y, but X is linked causally to Y; in (b), X and Z are linked causally to Y, but Z is not the cause of X; in (c), Z is a cause of both X and Y, but the effect of Z on Y is contained completely in X or mediated by X's influence on Y (Nie, Hull, Jenkins, Steinbrenner, & Bent, 1975). In diagrams (a), (b), and (c), the relationship between X and Y is considered causally closed to outside influences with respect to their covariation. In diagram (d), the covariation between X and Y is totally due to their direct common dependence on an outside cause, Z (Nie et al.). Finally, in diagram (e), the covariation between X and Y is caused partly by the dependence of Y on X and somewhat by their direct sharing of a common cause, Z (Nie et al.). In diagrams (d) and (e), the covariation between X and Y is not closed to outside influence (Nie et al.).

A path coefficient indicates the direct effect of one variable (assumed to be a cause) on another variable (assumed to be the effect). There are two types of path coefficients:

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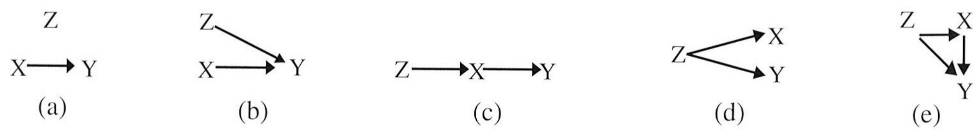

FIGURE 1. Baron and Kenny (1986) illustrate several different types of structures that express possible causal relationships underlying a covariation.

standardized and unstandardized. Standardized path coefficients (B) are standardized within a model because they are estimated from correlations. Standardized coefficients allow for comparisons among the relative importance of different variables tested. However, standardized coefficients are sample specific and therefore cannot be compared across samples or studies. Unstandardized coefficients (b) are affected by the measurement of the variable and cannot be used to infer the relative importance of a variable in a study. Authors sometimes use the term beta in place of standardized coefficient and beta in place of unstandardized coefficient; in this article, we use the terms interchangeably. Unstandardized path coefficients can be used to compare models across different samples. Therefore, standardized and unstandardized path coefficients should be presented. If only standardized are presented, then the standard deviations for all variables should be reported so that unstandardized coefficients can be calculated (Pedhazur, 1997).

Within the analysis, a regression is conducted for each variable in the model that is dependent or endogenous in relation to other variables. The model is then used to reproduce the correlation matrix, and this reproduced matrix is compared with the observed correlation matrix as one method to determine goodness of fit. Sometimes a researcher seeks to compare two slightly different models, perhaps a model with and one without a particular predictor. In the comparison, the best fitting of two or more models is selected by the researcher as the best model for advancement of theory (Garson, 2004).

Path analysis requires the usual assumptions that one commonly finds in regression. It is important to have an adequate sample size to determine and assess the significance of a path analysis. The recommended ratio is 20 cases per parameter (or variable measured) in the model (Klein, 1998). In general, the accuracy and stability of a path analysis declines with decreasing sample size as well as with an increasing number of variables.

Path analysis is particularly sensitive to model specification because, as in regressions, failure to include relevant causal variables or inclusion of extraneous variables often substantially affects the path coefficients, which researchers use to assess the relative importance of various direct and indirect causal paths to the dependent variable. Such interpretations should be undertaken in the context of comparing alternative models, after assessing their goodness of fit (Garson, 2004). Lea (1997) recommended testing for the significance of individual path coefficients by using the standard *t* or *F* test from regression output in addition to testing the overall path model with a goodness-of-fit test from a structural equation modeling program. A variety of goodness-of-fit indices are calculated when statistics software packages, such as LISREL (Hayduk, 1996; Jöreskog & Sörbom, 1984; Stage, 1990) or AMOS (Arbuckle, 1989), are used for path analysis.

Strengths and Weaknesses of Path Analysis

Path analysis as a methodology holds strength because it allows researchers to study direct and indirect effects simultaneously with multiple independent and dependent variables. A direct effect (see Figure 1, Example A) occurs when an independent variable affects a dependent variable. An indirect effect (see Figure 1, Examples C & E) occurs when an independent variable affects a dependent variable through a mediating variable (Baron & Kenny, 1986). Another strength of path analysis is that it allows the researcher to diagram a set of hypothesized relationships that can be translated directly into equations needed for the analysis.

Path analysis is not without its critics. "However convincing, respectable and reasonable a path diagram . . . may appear, any causal inferences extracted are rarely more than a form of statistical fantasy" (Everitt & Dunn, 1991). With path diagrams, the application of path analysis allows the researcher to compare the magnitude of the relationship between variables, which can lead to implications for the plausibility of prespecified causal hypotheses. However, path analysis cannot distinguish which of two distinct path diagrams is more correct, nor can it distinguish whether the correlation between A and B represents a causal effect of A on B, a causal effect of B on A, mutual dependence on other variables C, D, and so forth, or some mixture of these (Lea, 1997). Thus, theoretical knowledge on the part of the researcher is critical to the successful application of path analysis.

Lea (1997) noted several limitations that a researcher must keep in mind when using path analysis. First, one can use path analysis to evaluate the plausibility of theoretical hypotheses (in other words, validating a correlational relationship). Also, in some situations, one can use path analysis to test between two or more causal hypotheses, although it cannot establish absolutely the direction of causality. A causal path between two variables is given direction by the researcher, on the basis of theory. The results of the analysis can provide support (or refutation) of the hypothetical relationships expressed within the model. Second, path analysis is most useful when the researcher has a clear hypothesis to test, or a small number of hypotheses, all of which can be represented within a single path diagram. It is not an exploratory research procedure.

Third, a researcher cannot use path analysis in situations where feedback loops are included in the hypotheses: a theorized steady causal progression must be present across (or down) a path diagram. Nominal measurement, or ordinal measurements with few categories, including dichotomies, violates the assumptions of path analysis when the distributions are highly skewed, particularly for dependent variables; otherwise the analysis is often robust. Although some types of analyses will handle such variables, no standard ways exist that mix different kinds of analyses to produce the analogue of a path analysis (Lea, 1997).

Despite those limitations, the use of path analysis in social science research has allowed researchers to gain understanding and insight into important issues. Path analysis is not a means to accurately demonstrate causality between variables. It is a method for tracing the implications of a set of causal assumptions that the researcher is willing to impose on a system of relationships (Nie et al., 1975).

A Review of Existing Articles

To gain a better understanding of how path analysis has been applied by authors of articles published in *The Journal of Educational Research*, we review six articles in which this technique was used between 1992 and 2002. The benchmark used in selecting articles was simple: Researchers must have conducted at least one empirical analysis in the article to derive the path model and its associated path coefficients. A list of the six articles is found in the Appendix.

The research questions addressed in the articles include the (a) importance of self-efficacy on student confidence and performance (Pajares & Valiante, 1997; O'Brien, Martinez-Pons, & Kopala, 1999); (b) effect of part-time work on mathematics and science performance (Singh & Ozturk, 2000); (c) gender inequities in mathematics (Campbell & Beaudry, 1998); (d) effect of teacher communications, child achievement, parent education level, and parent ethnicity on parent involvement (Watkins, 1997); and (e) effect of student effort on schoolwork and school-based achievement (Brookhart, 1998). Analysis among the articles under investigation typically includes a combination of exogenous and endogenous variables such as gender, ethnicity, socioeconomic status (SES), parental educational attainment, and personality-related measures; and previous abilities, beliefs, and achievements. The objective of each study was to determine which of the relevant causal variables or exogenous variables significantly affected the variables of interest (endogenous variables). Researchers used path coefficients, along with the other statistical analyses, to assess the relative importance of various direct and indirect causal paths to the dependent variables.

To test the applicative research hypotheses, the authors of the six articles used several different conceptual frameworks to structure their models for analysis. Although not all the studies examined followed the guidelines and recommendations outlined below, all the authors are credited for making substantive contributions to their respective areas of study.

The following elements, specifically important to path analysis, should be surrounded by the ordinary and expected elements of any research paper, including:

1. A clear statement of purpose, a statement of questions to be answered;
2. A thorough review of the literature;
3. A clear description of the variables used in the study including means, standard deviations, correlations, treatment of missing data, and sample size.

Beyond those elements listed in the preceding paragraph, we evaluated the studies relative to the following criteria: (a) presentation of an explicit literature-based model for analysis, including discussion of omitted variables; (b) discussion of preliminary analysis that delineates the initial model, alterations to the model, including analysis of the superiority of the resulting model; (c) reported goodness of fit for all models tested; (d) illustration of paths between variables, standardized and unstandardized path coefficients, variance accounted for, and fit indices; and (e) discussion of results relative to other research, including limitations or biases in the study and suggestions for researchers. Table 1 provides a listing of all the essential elements of a path analysis report.

Presentation of an explicit literature-based model. Key to a path analysis is a clear presentation of a hypothetical model based on literature. The surrounding literature provides justification for inclusion of variables that provide connection to other models and extant research and identifies the unique contribution of the research at hand. Failure to set the analysis within the theoretical context can render a research project as useless as a mere mathematical exercise. Of the articles reviewed here, they all presented ample justification for their models on the basis of prior literature. Singh and Ozturk's (2000) model employed factors similar to prior research but used a longitudinal data set to examine

TABLE 1. Essential Elements of a Path Analysis Report

1. Explicit model based on literature
2. Discussion of all preliminary analyses
3. Report of fit indices for all examined models
4. Illustration of final model
5. Discussion of finding, relative to previous research

a familiar question. Brookhart (1998), on the other hand, added a new factor to a relatively older model. In a study of self-efficacy in writing, Pajares and Valiante (1997) used a familiar model with self-efficacy to study a new topic—writing composition. Similarly, O'Brien, Martinez-Pons, and Kopala (1999) examined self-efficacy by focusing on mathematics interest, but in a unique population—students in parochial high schools. Watkins' (1997) model employed factors that have been associated with child achievement and parental involvement. Finally, Campbell and Beaudry (1998) provided a loosely structured model based on factor analyses of large numbers of variables to examine differential effects of socialization agents on male and female students' views of mathematics.

Preliminary analysis and alterations to the model. Three of the articles provided extensive documentation of their analyses of the model. Brookhart (1998) reported exploration of alternative variables within the model and justification for using one measure over the other. Also, Pajares and Valiante (1997) reported preliminary analysis of the model, including details regarding specific programs and procedures and decisions regarding the analysis relative to theory. A third article (O'Brien, Martinez-Pons, & Kopala, 1999) described data fitting of their model and reported a Comparative Fit Index for the new model. Watkins (1997) reported a theoretical model and later a more revised model based on the explained observed correlations between the exogenous and mediating variables in the study. In addition, preliminary analysis for one article (Campbell & Beaudry, 1998) was extensive and required that interested readers consult a copy of a previously published article. In addition, analyses of outliers and creation of second-order factors were reported in the article. However, little detail was provided; it could have been added as an Appendix, which would have been helpful to other researchers, particularly novices who might have read such detail as a guide to their own decisions.

Goodness of fit for model(s) tested. Fit indices, indicating how well the model fits the information from the correlation matrices, are important for analysis of the model. Most of the articles did not include goodness-of-fit statistics for the models tested. All authors reported explained variance and either beta or effect sizes for significant paths. However, some authors reported only explained variance for the final exogenous factor and not the intervening exogenous variables. Only Pajares and Valiante (1997) provided extensive fit statistics. The authors provided chi-square, goodness-of-fit index adjusted for degrees of freedom, a normed fit index, and a nonnormed fit index in addition to explained variance. Finally, the authors compared chi-square statistics from early models with their final model to demonstrate better fit.

Illustration of paths between variables and coefficients. All the authors included a figure to illustrate either the proposed model or the final analyzed model with coefficients. Because most researchers ultimately produced models that included at least minor alterations to the initial model, the final model annotated with betas or effect sizes that most authors provided is preferred. The unstandardized betas can be used by researchers to represent the effect of one variable on another (Rosenthal, 1994). (As an example, see Figure 2.) If the direct effect of Z toward X were .07 and the direct effect of X toward Y were .06, then the indirect effect of X toward Z could be calculated manually by the researcher as being .0042.

By using the unstandardized betas, researchers can better compare previously calculated effect sizes between various studies. For further examples, see Campbell and Beaudry (1998) and Singh and Ozturk (2000).

Discussion, Limitations, and Recommendations

As with our earlier expectation, that path analysis reports present a literature-based model, all the articles reviewed provide extensive discussion of their findings within the context of the literature and research analyzing similar models. However, not all authors directly discussed limitations of their study. Exceptions were the two articles that explored self-efficacy in relation to other educational variables (Pajares & Valiante, 1997; O'Brien, Martinez-Pons, & Kopala, 1999). Those authors reminded readers of the controversy that surrounds the attribution of causality to correlation and cautioned that interpretations should be made cautiously. The authors also suggested ways in which the causal claims might continue to be tested. All articles contained recommendations, some that seemed explicitly directed to other researchers (Brookhart, 1998), others that seemed only to suggest future directions for the authors' own work or for the work of others (Watkins, 1997). One article included extensive discussion of the analysis for policy and the reality of student achievement (Singh & Ozturk, 2000).

An Illustration of Path Analysis

As an example, we show the analysis of a simple model (Figure 3) that explains high school students' participation in challenging mathematics courses. The model includes two exogenous variables that represent family composition, SES, and family structure; and three endogenous variables, eighth-grade mathematics achievement, mathematics attitude, and challenging mathematics units. Of course, in a research report for a journal, we would use the first 20–25% of the article to set the context for the study, review relevant

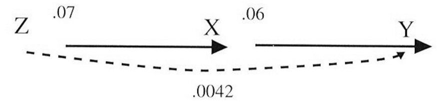

FIGURE 2. Illustration of paths between variables and coefficients.

literature, and present the model. Here, in the interest of space, we do not follow that convention.

We used a sample of public release data from a nationally representative data set that included family background, achievement tests, attitudes, and educational experiences measured every 2 years from Grade 8 to 12. Measurement of the variables is presented in Table 2.

Description of Example Model Tested

In the model, SES has a direct effect on challenging mathematics units, mathematics achievement, and mathematics attitude. Family composition has a direct effect on mathematics achievement and mathematics attitude. Mathematics attitude and eighth-grade mathematics achievement have a direct effect on challenging mathematics units. In the model, SES also has an indirect effect on challenging mathematics units through mathematics attitude. In other words, mathematics attitude is a mediating variable for the effect of SES on challenging mathematics units (see Baron & Kenny, 1986). Also, all of the variables are designated by a rectangle, which is a common visual depiction for observed variables.

SES is a composite of several variables and divided into

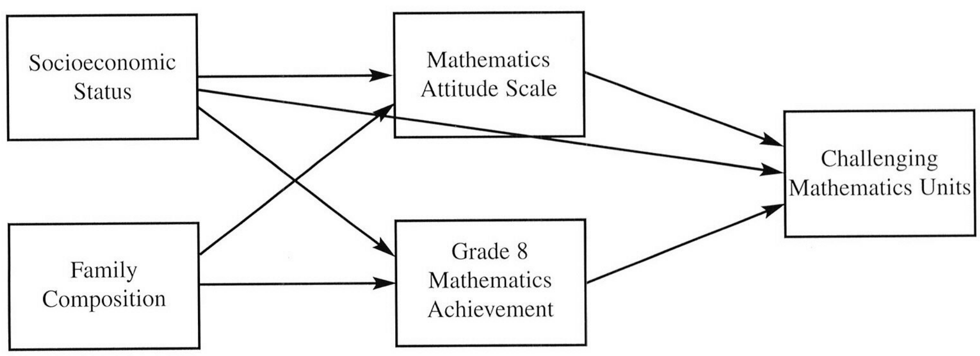

FIGURE 3. Challenging mathematics units path model.

TABLE 2. Measurement of Variables

Variable	Description
Socioeconomic status, by quartiles	SES was constructed from a questionnaire that elicited parents' income level, educational background, and occupation in 8th grade. This variable was then divided into quartiles (1–4, low to high).
Family composition	Family composition characterized the family or household composition in the 8th grade—whether the student lived in a two-parent (mother and father, step or natural) coded 1 home or had some other living arrangement, coded 0.
Eighth-grade mathematics achievement	Eighth-grade mathematics achievement score
Mathematics Attitude Scale	Perceptions and attitudes of student toward mathematics in 8th grade measured on a Likert-type scale (4 = *strongly agree* and 1 = *strongly disagree*) average of three items: (a) usually look forward to mathematics class, (b) mathematics will be useful in my future, (c) afraid to ask questions in mathematics class (reverse coded).
Challenging mathematics units	Challenging mathematics units by 12th grade was created by adding the number of units in the following variables: Algebra I, Algebra II, geometry, trigonometry, pre-calculus, and calculus.

Note. SES = socioeconomic status.

quartiles. Family composition is a dichotomous variable coded 1 for two-parent households (whether step or natural) and coded 0 for one parent, relative, or other. The mathematics achievement score used in this study was measured in the eighth grade as part of a test covering four subject areas—reading, history, mathematics, and science, in 11/2 hours of multiple-choice testing. Mathematics attitude was measured as the average of a Likert-type scale response (4 = *strongly agree* and 1 = *strongly disagree*) to three items: (a) Usually look forward to mathematics class, (b) mathematics will be useful in my future, and (c) afraid to ask questions in mathematics class. The ultimate outcome variable, challenging mathematics units, was created by adding the number of semester units in the following variables: units in Algebra I, units in Algebra II, units in geometry, units in trigonometry, units in precalculus, and units in calculus. We did not include many of the mathematics courses typically offered in high school that are not considered academic-track courses. (Table 3 presents means, standard deviations, and correlations for the sample.)

SES, mathematics attitude, and mathematics achievement accounted for 17% of the variance in challenging mathematics ($R^2 = .17$; Figure 4). The effects of the exogenous variables within the model were mixed. Although SES had a strong direct effect in mathematics achievement (.39), the effect of family composition was not significant. However, the effects of exogenous variables on attitudes regarding mathematics were the opposite. Family composition, but not SES, was statistically significantly related (.05) to mathematics attitude (see Table 4).

Although the model was statistically significant and explained a modest portion of the variance in challenging mathematics units, when we take all variables into account in this simple model, an unexplained variance of $E = .91$ is present. Therefore, it is likely that other factors not included in this model may have a significant effect on challenging

TABLE 3. Means, Standard Deviations (*SD*), and Correlations for Variables (N = 3,747)

Variable	Correlation 1	2	3	4	5	*M*	*SD*
1. Family composition	1	.152*	.096*	.043*	.109*	0.7337	0.4421
2. Socioeconomic status	.152*	1	.400*	–.016	.297*	2.7300	1.0880
3. Mathematics achievement score	.096*	.400*	1	.092*	.382*	46.9970	8.5073
4. Mathematics Attitude Scale	.043*	–.016	.092*	1	.103*	2.6002	0.4700
5. Challenging mathematics units	.109*	.297*	.382*	.103*	1	1.7491	1.1249

*Correlation is significant at the .01 level, one-tailed.

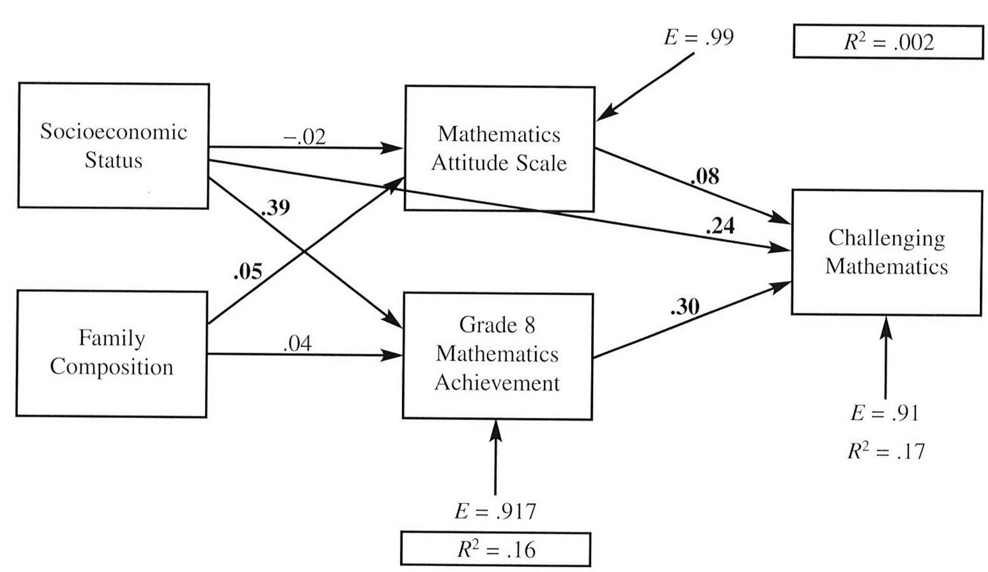

FIGURE 4. Challenging mathematics path model. Bold indicates statistically significant. Fit indices: root mean square error of approximation = 0.083. Tucker Lewis Index = 0.83.

mathematics and on any of the other endogenous variables examined.

Hu and Bentler (1999) provided a good review of goodness-of-fit indices. Kenny (2003) stated that for chi-square models with 75–200 cases, this is a reasonable measure of fit. Once the sample size increases past 200 cases, the chi-square is almost always statistically significant. For the Bentler Bonett Index or Normed Fit Index (NFI), a value between .90 and .95 is acceptable and above .95 is good (Kenny, 2003). The Tucker Lewis Index or Non-normed Fit Index (NNFI) has similar cutoffs as the NFI. The root mean square error of approximation (RMSEA) has a cutoff of .05, although less than .08 is acceptable. A confidence interval also can be calculated. We recommend using at least two fit indices. We used the Tucker Lewis Index (0.83) and the RMSEA (0.083, CI = 0.07, 0.10) as examples. Both examples indicate a poor fit and potential model modification.

At this point in the analysis, we discuss our findings in relation to what was described or discussed in the introduction, review of literature, and theoretical discussion of the model.

Path Analysis—Its Drawbacks

The strength of path analysis lies in its ability to decompose the relationships among variables and to test the validity of a theoretical perspective (or model). The use of the technique is predicated on a set of assumptions typical in ordinary least squares analysis that are somewhat restrictive in nature (Pedhazur, 1997). Those include the assumption that (a) variables used in testing a causal model through path analysis should be measured without error, (b) error terms (or residuals) are not intercorrelated, and (c) the flow of influence in the model is unidirectional. Although those conditions are highly desirable, the reality is that the assumptions are rarely, if ever, found in educational settings where nonexperimental research is more appropriate.

As most researchers have found, measures used to capture the conceptual meaning of constructs in a study (or model) almost always have a moderate degree of reliability. Even when classical approaches are used for establishing the reliability of different measures, the source of error is treated as random, and derived coefficients that are based on those premises are assumed correct. Many sources of error in measurement are systematic; although this does not affect the reliability of such measures, it does have an impact on the validity of the measures (Pedhazur, 1997).

Moreover, almost all variables of interest in educational research are not directly observable. Variables such as educational aspiration, test anxiety, student perceptions, and self-reported behaviors are latent constructs. The use of a single or few indicators to fully capture the complexities in

TABLE 4. Decomposition of Effects From Path Analysis

Effect	Unstandardized coefficient	*SE*	Standardized coefficient	*t*	R^2
Socioeconomic status (SES)	3.077	0.121	0.39	25.486*	.16*
Family composition on mathematics achievement	0.701	0.297	0.04	2.357	
SES	–0.01	0.007	–0.02	–1.426	0.002
Family composition on mathematics attitude	0.05	0.018	0.05	2.796*	
Mathematics achievement	0.049	0.002	0.30	23.918*	.17*
Mathematics attitude	0.17	0.037	0.08	4.599*	
SES on challenging mathematics	0.458	0.019	0.24	23.675*	

	Family composite	SES	Mathematics achievement	Mathematics attitude
Standardized direct effects				
Mathematics achievement	0.04	0.40	0.00	0.00
Mathematics attitude	0.05	–0.02	0.00	0.00
Challenging mathematics units	0.00	0.18	0.30	0.08
Standardized indirect effects				
Challenging mathematics units	0.02	0.12	0.00	0.00

*$p < .01$.

such a construct as required in path analysis is impractical. To fully encapsulate the nature of those variables requires the use of multiple indicators for each latent construct.

Another drawback of path analysis is that it does not permit the possibility of a degree of interrelationship among the residuals associated with variables used in the path model. Conceptually, that assumption is unsound in longitudinal studies in which individuals may be assessed at different points in time on identical variables. It is irrational to believe that error in the same variables for the same individuals at different times would not be interrelated.

Testing models that hypothesize a concurrent impact among variables is rare. The conceptualization of an investigation that centers on the feedback of one or more variables on each other is seldom, if ever, the intent of most educational studies, and the notion that there can be an influence from only one variable to another is unrealistic. Conceivably, academic experiences not only affect a student's academic performance but also the student's performance affects that student's academic experiences (e.g., studying, participating in study groups, accessing academic resources, engaging in classroom discussion). However, the use of path analysis to address such issues is not appropriate.

Summary

Path analysis is a popular method for social science analysis. We briefly described the technique and issued a caution about the attribution of causality to correlational relationships. Initially, we provided suggestions for path analysis reporting criteria, then we evaluated articles from the last decade that were published in *The Journal of Educational Research* and that employed the procedure. Next, we described limitations of path analysis. We reviewed path analysis articles that were published in *The Journal of Educational Research* in the last decade and, finally, presented a sample analysis. We hope that this article, and the references to the previous decade's research, will serve as a reference for future authors, as well as reviewers, as they seek answers to their own educational questions.

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APPENDIX
List of Path Analysis Articles Reviewed

Brookhart, S. M. (1998). Determinants of student effort on schoolwork and school-based achievement. *The Journal of Educational Research, 91,* 201–209.

Campbell, J. R., & Beaudry, J. S. (1998). Gender gap linked to differential socialization for high-achieving senior mathematics students. *The Journal of Educational Research, 91,* 140–147.

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