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ABSTRACT

Path analysis is presented as a technique that can be used to test on a priori model based on a theoretical conceptualization involving a network of selected variables. This being an introductory source, no previous knowledge of path analysis is assumed, although some understanding of the fundamentals of multiple regression analysis might be helpful. Included is a summary of some of the basic procedures involved in performing a path analysis, as well as a discussion of path diagrams, path coefficients, and model testing with path analysis. Additional references, with annotations, to more advanced and detailed discussions of path analysis are also included. The procedure of path analysis is summarized as follows: (1) formulate a theoretical conceptualization of the causal structure for the relevant variables, and construct a path diagram representing your theoretical causal structure; (2) calculate the path coefficients using regression analysis; (3) decompose the bivariate relationship into direct and indirect causal components; (4) delete those paths from the model that were found to be nonsignificant, and reconstruct the original correlation matrix from the modified path model; (5) note the discrepancies between the original and the reconstructed correlation coefficients, and retain or reject the proposed model based on the nature and the number of these discrepancies. (Author/CTM)

Path Analysis: A Brief Introduction[1]

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The purpose of path analysis

The method of path analysis was developed by the geneticist Sewall Wright in the early 1920's. In one of his earliest papers on path analysis, Wright (1921) summarized the general method of path analysis in the following manner:

> The present paper is an attempt to present a method of measuring the direct influence along each separate path in such a system and thus of finding the degree to which variation of a given effect is determined by each particular cause. *The method depends on the combination of knowledge of the degrees of correlation among the variables in a system with such knowledge as may be possessed of the causal relations.* In cases in which the causal relations are uncertain, the method can be used to find the logical consequences of any particular hypothesis in regard to them. (p. 557, my italics)

In a series of subsequent papers, Wright further elaborated on the purpose of path analysis:

> ...the method of path coefficients is not intended to accomplish the impossible task of deducing causal relations from the values of the correlation coefficients. (1934, p. 193)

> ...*Path analysis is an extension of the usual verbal interpretation of statistics, not of the statistics themselves.* It is usually easy to give a plausible interpretation of any significant statistic taken by itself. *The purpose of path analysis is to determine whether a proposed set of interpretations is consistent throughout.* (1960b, p. 444, my italics)

In summary, the major purpose of path analysis is to test an a priori causal model based on the researcher's conceptualization of the relationship among the relevant variables. Path analysis is not a technique for discovering "causes." Path analysis is a method to assess whether the empirical correlations among ~~the relevant variables~~ are consistent with the causal model proposed by the researcher. As stated by Kerlinger and Pedhazur (1973), "...path analysis is useful in theory testing rather than generating it" (p. 305). In short, path analysis is to be used as an aid to supplement the researcher's thinking, and not as a substitute for such thinking.

Drawing the path diagram

Prior to performing the actual path analysis, it is usually necessary to construct a path diagram. A path diagram (see Figure 1) is a graphic representation of the causal model based on the researcher's conceptualization of the relevant variables. Although it is not actually required for a numerical path analysis, path diagrams can be extremely useful in assisting the researcher in organizing the relevant variables within the causal model.

It is important to note that there is nothing "magical" about the path diagram in discovering causes. The researcher's specific path diagram represents only one of the possible ways the variables might be structured. Thus, any particular path diagram simply represents the researcher's specific conceptualization of the relevant variables.

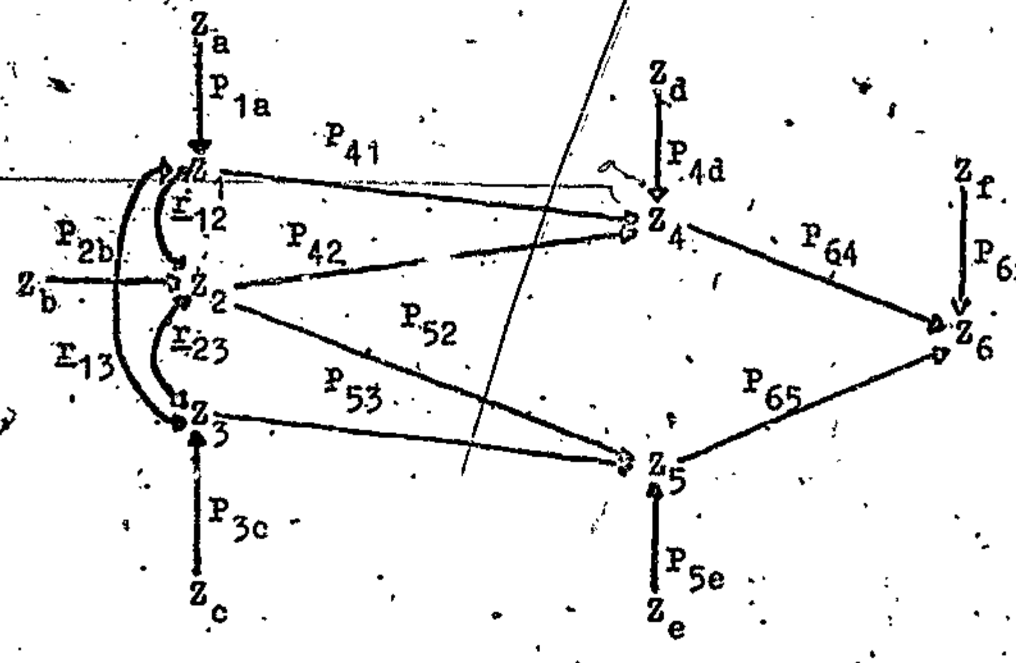

Figure 1

Variables in the path diagram

The path diagram contains three type of variables: exogenous, endogenous, and residual variables. The exogenous variables are those variables whose causal variation is assumed to be determined by variables outside the causal model. That is, no attempts have been made to explain the variability of the exogenous variables. Variables Z_1, Z_2, and Z_3 are examples of exogenous variables in the path diagram presented in Figure 1. It is possible for exogenous variables to be correlated among themselves. However, no attempt is made to explain the correlation.

Endogenous variables are those variables in the path diagram whose total cause or variability is assumed to be completely determined by some linear combination of variables within the causal model. Thus, the variability of any particular enodgenous variable may be determined by either exogenous variables and/or other endogenous variables specified within the causal model. Variables Z_4, Z_5, and Z_6 are examples of endogenous variables in Figure 1.

Residual variables are those that are introduced into the system to account for any variation in other variables under consideration not explained by the causal model. They are used to indicate the effects of variables not included in the model. Residual variables, and their causes, are assumed to be unknown. In one sense, the variability accounted for by the residual variables could be labeled as error variance. Residual variables are assumed to be uncorrelated with other residual variables and with the other variables specified in the causal model. Variables Z_a through Z_f are examples of residual variables presented in Figure I.

Basic rules for drawing path diagrams

Although each path diagram represents a unique way of structuring a set of variables, there are certain basic rules that all path diagrams must conform to. A few basic rules are (Land, 1969):

1. That the postualted causal relationships among variables within the path diagram are represented by unidirectional arrows from the causal variable to the effect variable. For example, in Figure 1 the arrows leading from Z_4 and Z_5 to Z_6 indicate that both Z_4 and Z_5 (the causal variables in this case) have an influence (determine some of the variability) in Z_6 (the effect variable in this case).
2. That the postulated noncausal (unexplained) relationships among the exogenous variables are represented by two-headed curvilinear arrows connecting the exogenous variables. For example, in Figure 1 the noncausal or unexplained relationship between the exogenous

variables Z_1 and Z_3 is indicated by a curved two-headed arrow connecting them. The two-headed arrow indicates that it is not known which of the two exogenous variables is the causal variable and which is the effect variable in this particular relationship. More simply stated, the direction of the causal flow is unknown.

3. The influence of the residual variables is also represented by unidirectional arrows extending from the residual variable to the specific variable under consideration. For example, in Figure 1 the unidirectional arrow connecting the residual variable Z_f with Z_6 represents the influence of Z_f on the endogenous variable Z_6.

4. The symbol P_{41} represents the path coefficient (to be discussed in more detail in the next section). The path coefficient represents a numerical value of the postulated causal influence of the causal variable on the effect variable. The first subscript of the path coefficient denotes the effect variable in question. The second subscript deontes the causal variable in question. In Figure 1, for example, the path coefficient P_{41} represents the numerical value of the causal influence of Z_1 on Z_4. Since the causal flow of the path diagram is unidirectional, the path coefficients of the nature P_{41} and P_{14} are not permissible in the same diagram.

In summary, the first step in performing a path analysis involves constructing a path diagram, according to the basic rules, illustrating the causal structure among the relevant variables based on ~~the~~ researcher's particular theoretical conceptualization.

The second step in performing a path analysis involves calculating the numerical values of the path coefficients.

Calculating the values of the path coefficients

Path coefficients

Wright (1934) defined path coefficients as:

> The fraction of the standard deviation of the dependent variable (with the appropriate sign) for which the designated factor is directly responsible, in the sense of the fraction which would be found if this factor varies to the same extent as in the observed data while all others (including the residuals factors...) are held constant. (p. 162)

In brief then, a path coefficient is an index of the direct influence of a particular variable, either an exogenous or endogenous variable, on a designated endogenous variable, with all other variables in the causal model held constant. Based on this defination, the squared path coefficient represents an index of the proportion of the variance of the endogenous variable for which the designated causal variable is directly responsible.

Conceptually the path coefficient and the partial correlation are very similar. However, unlike the partial correlation, the path coefficient is used within the causal system to suggest how particular variables might influence one another according to some theoretical interpretation.

In order to discuss how to calculate path coefficients, first it may be important to briefly consider the basic structural model of path analysis. The basic structural equation of the path model is that each endogenous variable can be represented by a linear combination of those variables that have a direct influence on it (e.g., connected to it by unidirectional arrows) multiplied by their respective path coefficients (the index of the direct influence). For example, the structural equations representing Z_4, Z_5, and Z_6 can be expressed as

$$Z_4 = P_{41}Z_1 + P_{42}Z_2 \qquad \text{Eq. 1}$$

$$Z_5 = P_{52}Z_2 + P_{53}Z_3 \qquad \text{Eq. 2}$$

$$Z_6 = P_{64}Z_4 + P_{65}Z_5 \qquad \text{Eq. 3}$$

The first step in obtaining the path coefficients for a particular equation is to perform a regression analysis in which you regress the specific endogenous variable on each of the causal variables that have a direct influence on it. To obtain the path coefficients for Eq. 3 you would regress variable Z_6 on variables Z_4 and Z_5. To calculate the path coefficients for Eq. 1 and Eq. 2, separate regression analyses for variables Z_4 and Z_5 would also be required. One regression analysis would be to regress Z_4 on variables Z_1 and Z_2. The other regression analysis would be to regress Z_5 on Z_2 and Z_3.

Calculation of the actual value of the path coefficient (P_{ij}) is based on the regression coefficients (unstandardized regression coefficients or B-weights) obtained from the regression analysis. The formula for calculating the value of the path coefficient (or the standardized path coefficient, as they are sometimes referred to) form the regression coefficient is shown in Eq. 4.

$$P_{ij} = B_{ij}\ (\sigma_j/\sigma_i) \qquad \text{Eq. 4.}$$

If the computer program performing your regression analyses provides both regression coefficients and standardized regression coefficients (or beta weights), the standardized regression coefficients (β) can be directly substituted for the path coefficient value.

$$\beta_{ij} = B_{ij}\,(\sigma_j/\sigma_i) = P_{ij} \qquad \text{Eq. 5}$$

It is also important to note that when dealing with standardized scores the path coefficients will equal the regression coefficients.

$$P_{z_i z_j} = B_{z_i z_j}\,(\sigma_{z_j}/\sigma_{z_i}) \qquad \text{Eq. 6}$$

In those particular cases where you are regressing an endogenous variable on a single causal variable, the path coefficient will equal the zero-order correlation coefficient between the two variables.

$$P_{ij} = \underline{r}_{ij} = B_{ij}\,(\sigma_j/\sigma_i) = \beta_{ij} \qquad \text{Eq. 7}$$

Since the nature of the causal relationship between the exogenous variables is unknown, the zero-order correlation coefficient between them is used to indicate the numerical value of those noncausal (unknown) relations in the path diagram. These values are obtained from the original correlation matrix. For example, the numerical value for the non-causal relationship between Z_2 and Z_3 in Figure 1 would be $\underline{r}_{23}$.

Decomposing the proposed causal structure

One of the major advantages of path analysis is that it allows you to decompose the proposed causal relationship between the variables into direct and indirect causal effects. The direct effect of a causal variable is the influence that a variable has on a specific endogenous variable, with all the other variables in the model held constant. As stated earlier, the value of the direct causal effect is represented by the path coefficient. The indirect causal effect refers to the extent to which a particular variable produces a change in an endogenous variable indirectly by causing a change in an intervening or mediating variable. In Figure 1 the direct causal effect of

Z_1 on Z_4 is represented by P_{41}. The indirect effect of Z_1 on Z_4 can be expressed by tracing changes in Z_1 that produce a change in Z_2, which in turn also produces a change in Z_4. Thus, the effect Z_1 has on Z_4 can also be expressed through its intervening relationship with Z_2. This type of interpretation is one of the major advantages of path analysis.

An illustration of a general decomposition table is presented in Table 1. An example illustrating the decomposition of the relationship between Z_1 and Z_4 is also presented in Table 1.

Table 1

Decomposition Table

Bivariate Relationship	Total Covariance(A)	Causal Direct (B)	Causal Indirect (C)	Causal Total (D)	Noncausal (E)
Z_4Z_1	r_{41}	P_{41}	P_{41} r_{12}	B + C	A - D

The column labeled Bivariate Relationship in Table 1 represents a listing of the two variables whose causal relationship is being decomposed. The column labeled Total Covariation (A) lists the zero-order correlation coefficient between the two variables.

The Causal portion of the decomposition table is subdivided into Direct (B), Indirect (C), and Total (D) columns. The value listed under the Direct column represents the direct influence of the causal variable on the effect variable, or the path coefficient. The value listed under the Indirect column represents the indirect influence of the causal variable. The value of the indirect causal effect is the sum of the products of all the coefficients along the paths leading from the caus variable to the effect variable. Rules for calculating the indirect effects will be discussed in the next section. Finally, the value listed under the Total (D) column represents the total causal influence of the particular causal variable on the specific effect variable. The value indicating the total causal effect is obtained by adding the direct and indirect causal values.

The value in the Noncausal column (E) represents the influence of variables outside the model (viz., residual variables). This value is obtained by subtracting the total causal value from the total covariation value (A - D = E).

Being able to decompose the correlation of a bivariate relationship into the direct and indirect influence allows the researcher to interpret if the causal relationship between two variables is a real one or a spurious one mediated through the influence of other intervening variables. For example, the influence of Z_4 and Z_5 on Z_6 could actually be a result of their shared influence with Z_2. That is, changes in Z_2 produces changes in both Z_4 and Z_5, which in turn result in changes in Z_6.

Another numerical index that is informative when interpreting the decomposition of a causal relationship, although not usually listed in the decomposition table, is the coefficient of alienation (Eq. 9). This indicates the proportion of variance in the effect variable that is not accounted for by the causal variables in the path model.

$$P_{ia} = \sqrt{1 - R^2} \qquad \text{Eq. 9}$$

In Eq. 9 the subscripts i and a represent the effect variable and the particular residual variable (composite of unknown variables), respectively. R^2 represents the multiple correlation of all the variables in the model that have a direct influence on the particular effect variable.

Tracing paths and compound path coefficients

Being able to decompose the bivariate relationship into direct and indirect effects often times requires the calculation of compound path coefficients. A compound path coefficient is the product of a series of connecting path coefficients. Calculating compound path coefficients is based on tracing the paths connecting the two variables of interest. An example of a compound path in Figure 1 would be the connecting paths between Z_2 and Z_4. One such compound path would be

$$Z_2 \xrightarrow{P_{42}} Z_4 \xrightarrow{P_{64}} Z_6.$$

The value of the compound path coefficient (P_{62}) for the connecting paths between Z_2 and Z_6 illustrated above would be the product of the separate path coefficients.

$$P_{62} = P_{42} \cdot P_{64}$$

The tracing of paths and the calculation of compound path coefficients is of particular relevance to the calculation of the value for the indirect causal effect component. The value of the indirect causal effect component is the sum of all the compound path coefficients connecting the two variables of interest. As is suggested in the previous sentence, often times there is more than one indirect path connecting two variables. For the Z_3Z_4 relationship, for example, there are two different indirect connecting paths:

$$Z_3 \xrightarrow{r_{23}} Z_2 \xrightarrow{P_{42}} Z_4 \qquad P_{43} = r_{23} \cdot P_{42} \qquad \text{(a)}$$

$$Z_3 \xrightarrow{r_{13}} Z_1 \xrightarrow{P_{41}} Z_4 \qquad P_{43} \quad r_{13} \quad P_{41} \qquad \text{(b)}$$

The value of the indirect effect in this relationship would be the sum of the two separate compound path coefficients (a + b).

$$\text{indirect effect value} = r_{23} \cdot P_{42} + r_{13} \cdot P_{41}$$

Tracing paths and calculating compound path coefficients is not an arbitrary process. The remainder of this section will briefly discuss some of the more important rules for tracing paths within the causal model. (A more extensive discussion of the rules for tracing paths can be found in Li (1975).)

Rules for tracing paths

1. When tracing paths it is permissible to move backwards along a connecting path, and then in a forward direction along the next path. Moving forward, then backwards is not permissible.

$$Z_4 \xleftarrow[\text{backward flow}]{} Z_2 \xrightarrow[\text{forward flow}]{} Z_5 \quad \text{is permitted}$$

$$Z_4 \xrightarrow[\text{forward flow}]{} Z_6 \xleftarrow[\text{backward flow}]{} Z_5 \quad \text{is not permitted}$$

2. Connecting paths (or compound path coefficients) should not contain more than one correlation coefficient.

$$Z_3 \xrightarrow{r_{23}} Z_2 \xrightarrow{P_{42}} Z_4 \quad (r_{23} \cdot P_{42}) \quad \text{is permissible}$$

$$Z_3 \xrightarrow{r_{23}} Z_2 \xrightarrow{r_{12}} Z_1 \xrightarrow{P_{41}} Z_4 \quad (r_{23} \cdot r_{12} \cdot P_{41}) \quad \text{is not permissible}$$

3. That in a particular compound path the same variable cannot be passed through more than once.

4. A compound path coefficient is equal to the product of the connecting path coefficients.

5. The correlation between two variables is equal to <u>the sum of the products of the path coefficients for all the connecting paths between the two variables, including both direct and indirect paths</u>. For example, the correlation between Z_1 and Z_6 can be expressed as

$$\underline{r}_{16} = p_{41} \cdot p_{64} + \underline{r}_{12} \cdot p_{42} + \underline{r}_{12} \cdot p_{52} \cdot p_{65} + \underline{r}_{13} \cdot p_{53} \cdot p_{65}.$$

Other mathematical mnemonics for calculating the correlation coefficients can be found in Land (1969), Li (1975), and Kerlinger and Pedhazur (1973).

In brief summary, the third step in performing a path analysis is the decomposition of the bivariate relationships into direct and indirect causal components. This decomposition is performed by tracing paths within the model according to certain basic rules. The major advantage of this decomposition process is that it makes possible the assessment of whether the relationship between variables is a real one or a spurious one mediated through the indirect influence of other variables.

<u>Theory (Model) testing</u>

Path analysis is a hypothesis testing technique that allows you to test whether or not the proposed causal model is consistent with the empirical correlations among the relevant variables. A path model is tested by attempting to reconstruct the original correlation matrix from the path coefficients. A comparison is then made between the original correlation matrix and the reconstructed correlation matrix. If the discrepancies between the two matrices are small, support for the proposed model has been found. If the discrepancies are large, the model is not supported, and therefore rejected.

It is always possible to reproduce the original correlation matrix from any model when all the connecting paths and the path coefficients are present. Because of this, simply having the completed path model is of little theoretical significance.

To test a particular path model requires the researcher to "trim down" or simplify the path model by deleting certain paths from the model, and then attempting to reconstruct the original correlation matrix. There are numerous criteria by which connecting paths may be deleted from the model. Paths can be deleted after the decomposition indicates that the direct effect was relatively small or statistically nonsignificant (e.g., $p < .05$). Paths may be deleted if the decomposition indicates that the effect of a particular variable was actually mediated through the indirect influence of other variables. Paths may also be deleted or retained, inspite of there level of significance. depending on how theoretically relevant the researcher perceives them to be.

As stated earlier, the test of a path model is the extent to which the original correlation matrix can be reconstructed from the "trimed down" model. If the discrepancies between the original and the reconstructed matrix are small (e.g., $p < .05$) and few in number, the path model is said to be one possible explanation for the causal relationship among the variables in question. Land (1973) has recently developed a statistical test to assess the overall goodness of fit of the reconstructed correlation matrix with the original matrix.

As noted earlier, a path model represents only one of many possible ways a set of variables can be structured. Finding that a particular path model results in small discrepancies from the original matrix does not permit the conclusion that the proposed model is the correct one for describing the causal structure of the variables in question. Therefore, path analysis is more of a method for rejecting models that for lending support to one of many competing causal models (Kerlinger & Pedhazur, 1973).

In brief summary, the fourth step in performing a path analysis involves trimming down the proposed path model by deleting paths not found to be significant, meaningful, and/or theoretically relevant. After the path trimming procedures are completed, an attempt is made to reconstruct the original correlation matrix from the revised path model. Small discrepancies between the original and the reconstructed correlation matrix provides support that the proposed model is consistent with the data. It does not allow for the conclusion that the model is the correct one for describing the structural relationship among the variables.

Assumptions of path analysis

Path analysis is guided by a set of basic assumptions. The assumptions most relevant to the present discussion of path analysis include:

1. The relationships among the variables in the model are linear and additive. Therefore, curvilinear, multiplicative, or interaction relations are excluded. It is possible to perform a path analysis on variables with nonlinear relationships if the range of the values of interest is linear. In addition, in many cases it is possible to use a number of conventional transformations to transform the data to meet the linear requirement (Heise, 1969);

2. That the variables in the model be measured on an interval scale. It is possible to do a path analysis with ordinal measures (boyle, 1970). Although the usage of dummy variables for performing regression analysis also permits a weakening of the interval measure assumption.

It also is permissible to include composite variables in the path model, as long as the separate variables in the composite are highly correlated and they do not influence the specific effect variable differentially.

3. That the residual variables are uncorrelated among themselves and with other variables in the path model.
4. That there is a one-way causal flow in the system. That is, reciprocal causation between the variables is ruled out.

Path analysis in a capsule

Step 1

Formulate a theoretical conceptualization of the causal structure for the relevant variables.

Construct a path diagram representing your theoretical causal structure.

Step 2

Calculate the path coefficients using regression analysis.

Step 3

Decompose the bivariate relationship into direct and indirect causal components.

Step 4

Delete those paths from the model that were found to be statistically nonsignificant, not meaningful, and/or theoretically irrelevant.

Reconstruct the original correlation matrix from the modified path model.

Note the discrepancies between the original and the reconstructured correlation coefficients.

Make your decision to retain or reject the proposed model based on the nature and the number of these discrepancies.

References and Recommended Readings

Boyle, R. P. Path analysis and ordinal data. American Journal of Sociology, 1960, 75, 461-480.

A very interesting article in that it demonstrates the absence of any serious consequences when the assumption of interval measure in path analysis is violated. This discussion is supplemented with several examples.

Ducan, O. D. Path analysis: Sociological examples. American Journal of Sociology, 1966, 72, 1-16.

This source presents a very brief introduction on the logic of path analysis. This source is most useful with respect to the various examples presented of how path analysis has been used in sociological research. These examples are very illustrative of the technique.

Kerlinger, F. N., & Pedhazur, E. J. Multiple regression in behavioral research. New York: Holt, Rinehart, & Winston, Inc., 1973.

This source includes a very good summary of the basic principles of path analysis. The material in the text is supplemented by some very illustrative examples of how to perform a path analysis. Also included is a rather comprehensive coverage of the area of multiple regression analysis.

Heise, D. R. Problems in path analysis and causal inference. In E. F. Borgatta (Ed.), Sociological methodology. San Francisco: Jossey-Bass Inc., 1969.

An excellent presentation of many of the issues related to path analysis. Of particular interest is the section on the weakening of the assumptions of path analysis. A good, easy to read introduction to many important issues.

Land, K. C. Principles of path analysis. In E. F. Borogatta (Ed.), Sociological methodology. San Francisco: Jossey-Bass Inc., 1969.

An extremely comprehensive presentation of the topic of path analysis at the introductory level. Many of the basic principles of path analysis are very well presented. Included are a mnuber of examples to supplement the conceptual material presented.

Land, K. C. Identification, parameter estimation, and hypothesis testing in recursive sociological models. In A. S, Goldberger & O. D. Ducan (Eds.), Structural models in the social sciences. New York: Seminar Press, 1973.

This source discusses a statistical technique developed to test whether the discrepancy between the original and reconstructed correlation coefficients as a whole is beyond chance.

Li, C. C., Path analysis: A primer. Pacific Grove, CA: Boxwood Press, 1975.

A complete and up-to-date presentation of path analysis available. All aspects of path analysis are discussed in a manner that can be appreciated by both the novice or those very familiar with path analysis. In addition to the extensive coverage of path analysis, also presented are a few introductory chapters on correlation, regression, and multiple regression as they are related to path analysis. This source is particularly informative with respect to the rules for decomposing path coefficients, tracing paths, and reconstructing correlation coefficients.

Nie, N. H., Hull, C. H., Jenkins, J. G., Steinbrenner, K., & Bent, D. H. Statistical package for the social sciences (2nd Ed.), New York: McGraw-Hill, 1975.

A very good introductory summary of the basic principles of path analysis. Also provided is a very helpful discussion of how the SPSS program can be used when performing a path analysis.

Wright, S. Correlation and causation. Journal of Agricultural Research, 1921, 20, 557-585.

One of Wright's earliest papers on path analysis. A fairly good introduction to many of the basic principles of path analysis.

Wright, S. The method of path coefficients. Annals of Mathematical Statistics, 1934, 5, 161-215.

A revision of some of Wright's earlier works on the subject of path analysis. Included is a discussion of many of the basic principles of path analysis.

Wright, S. The treatment of reciprocal interaction, with or without lag, in path analysis. Biometrics, 1960, 16, 423-445. (b)

A discussion of some of the basic issues involved in the usage of path coefficients and path analysis.