

## Basic Concepts of Fit with Mediation Path Models

In mediation analysis, it can be shown that the correlation between a predictor and outcome variable is theoretically equal to the product of the correlation between the predictor variable and the mediator times the correlation between the mediator and the outcome (Baron & Kenny, 1987). This is easier to show visually.<sup>1</sup>



Putting this statement into a formula, we have:

$$r_{AC} = (r_{AB})(r_{BC})$$

Assume that  $r_{AB} = .3$ ,  $r_{BC} = .4$ , and  $r_{AC} = .6$ . Based on the formula above, however, the value of  $r_{AC}$  that is implied is .12 (i.e., .3 times .4). The data then are not in agreement with the value that for  $r_{AC}$  that is implied by the model.

This logic is the basic idea behind model fit in structural modeling. The correlations that are obtained from the data are compared to those values implied by the model. In essence, then, there is an *implied* correlation matrix. In actual practice, however, we usually use covariances—thus, the obtained and the implied covariance matrices are compared. The hypothesized model is evaluated by “fitting” the covariances obtained to the covariances implied by the model.

Now, assuming just three variables, there are 9 possible theoretical models one can draw (see next page).<sup>2</sup> By drawing out these models, computing implied correlations, and comparing them to obtained correlations, one discovers several interesting things.

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<sup>1</sup> This statement assumes several things including perfectly measured variables, population values, and no other mediating variables.

<sup>2</sup> This example is based on one by Steve West.

For this example assume that  $r_{AB} = .3$ ,  $r_{BC} = .4$ , and  $r_{AC} = .12$ .

Theoretical Model	Implied Correlation between Predictor and Outcome	Obtained Correlation	Does It Fit?
A → B → C	.12	.12	yes
A → C → B	.048	.3	no
B → A → C	.036	.4	no
C → B → A	.12	.12	yes
B → C → A	.036	.3	no
C → A → B	.048	.4	no
A → B A → C	.036	.4	no
B → A B → C	.12	.12	yes
C → A C → B	.048	.3	no

There are several things to notice. First, some models can be rejected as being inconsistent with the model. Second, not all models can be eliminated, because some fit equally well. Third, one can think about some conditions in which models could be ruled out because the model includes variables that are unlikely to be influenced by other factors (e.g., race, gender).

This example has implications for causal inference in so far as model fitting can assist in rejecting alternative causal models, even when those models are all based on cross-sectional data. In actual practice, however, several things must be kept in mind. These examples assume there are no other (fourth) spurious variables omitted that might account for the relationships obtained. With sample data, there is always sampling variability in estimating covariances (or correlations), and, thus, even for correct models, there is likely to be some lack of fit between what is implied and what is obtained.