Implementing an expanded mediation model to obtain less biased estimates of mediation effects using structural equation modeling.

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Background

It would be difficult to find a more cited article than the original Baron & Kenny (1986) manuscript elaborating the mediation analysis approach using a set of linear regression models. This approach is frequently used with data from both experimental and observational studies. However, Shrout, Keyes and Ornstein (2011) recently reminded psychopathology researchers that the validity and interpretability of this approach is contingent on a well-established temporal ordering of the model variables and the assumption of zero correlation between the residuals of the mediator and outcome variable.

Aim

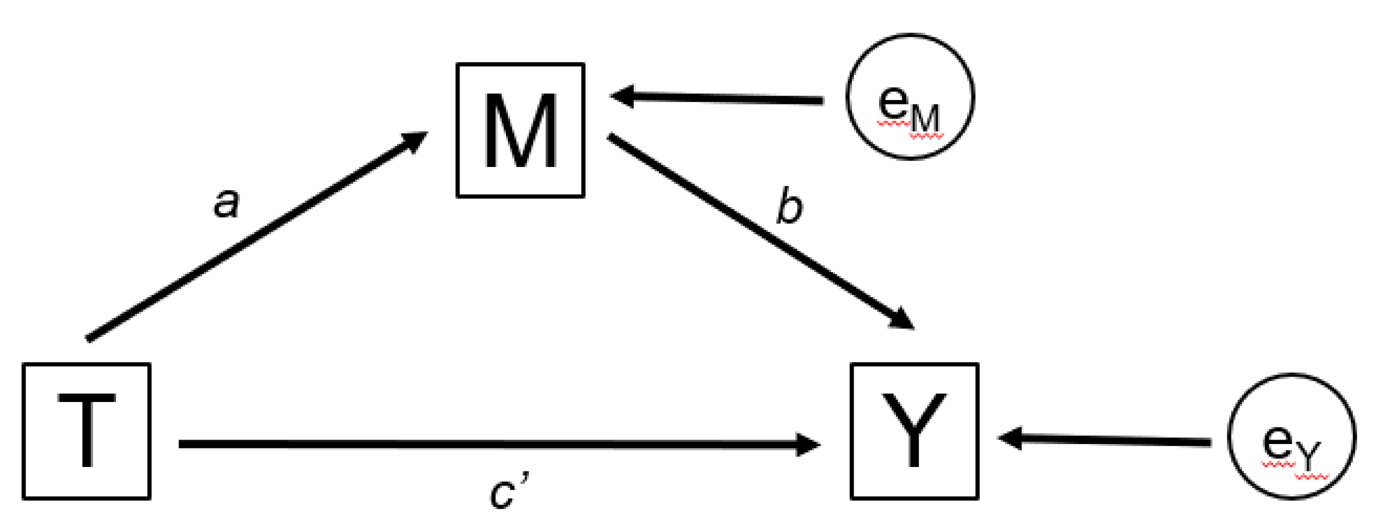
Our poster will document an expanded mediation model using structural equation modeling as implemented in MPlus software.

Method

The model being presented was estimated using data from a randomized clinical trial of primary care patients (n=179). Data were collected at baseline, 2, 4 and 6 months after randomization. The mediator was measured at 4 months and the outcome variable at 6 months post randomization. We obtained permission to use the dataset for methodological illustration purposes only, therefore no substantive specific conclusions will be made. In our illustration we will use generic names for all variables to maintain anonymity of the peer reviewed published study.

Classic mediation model

The classical mediation model includes an experimental treatment or an exposure in observational studies, a mediator variable and an outcome variable. The model is used to evaluate if treatment or exposure influences the outcome variable and to decompose such an effect into direct and indirect effects. Indirect effects are attributed to treatment or exposure induced changes in the mediator variable. If *a* is the effect on the mediator and *b* is the effect of the mediator on the outcome variable, the indirect effect would be their product *a X b.*

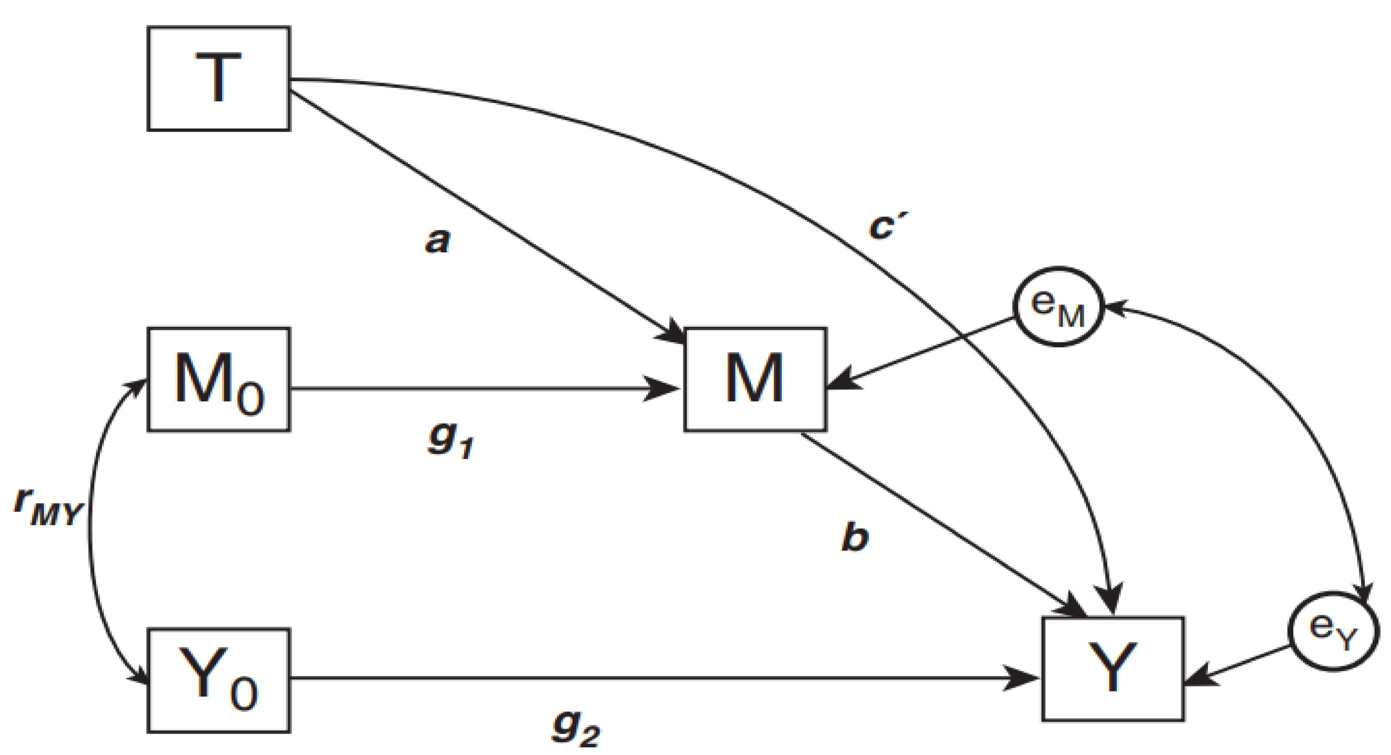


Estimating the significance and magnitude of such an effect is the primary goal of mediation analysis MacKinnon (2008). Such models help us understand the mechanism by which treatment or natural exposures affect the outcome variable of interest.

The expanded mediation model uses data frequently available but not incorporated into the mediation model. The expanded model achieves identification of a possibly important source of confounding not identified in the classic mediation model. In the expanded model this source of bias can be estimated and controlled for, producing a less biased estimate of indirect effects by incorporating baseline measures for the outcome and mediator variable. If the model shows adequate fit, it improves the validity and precision of results from mediation analysis.

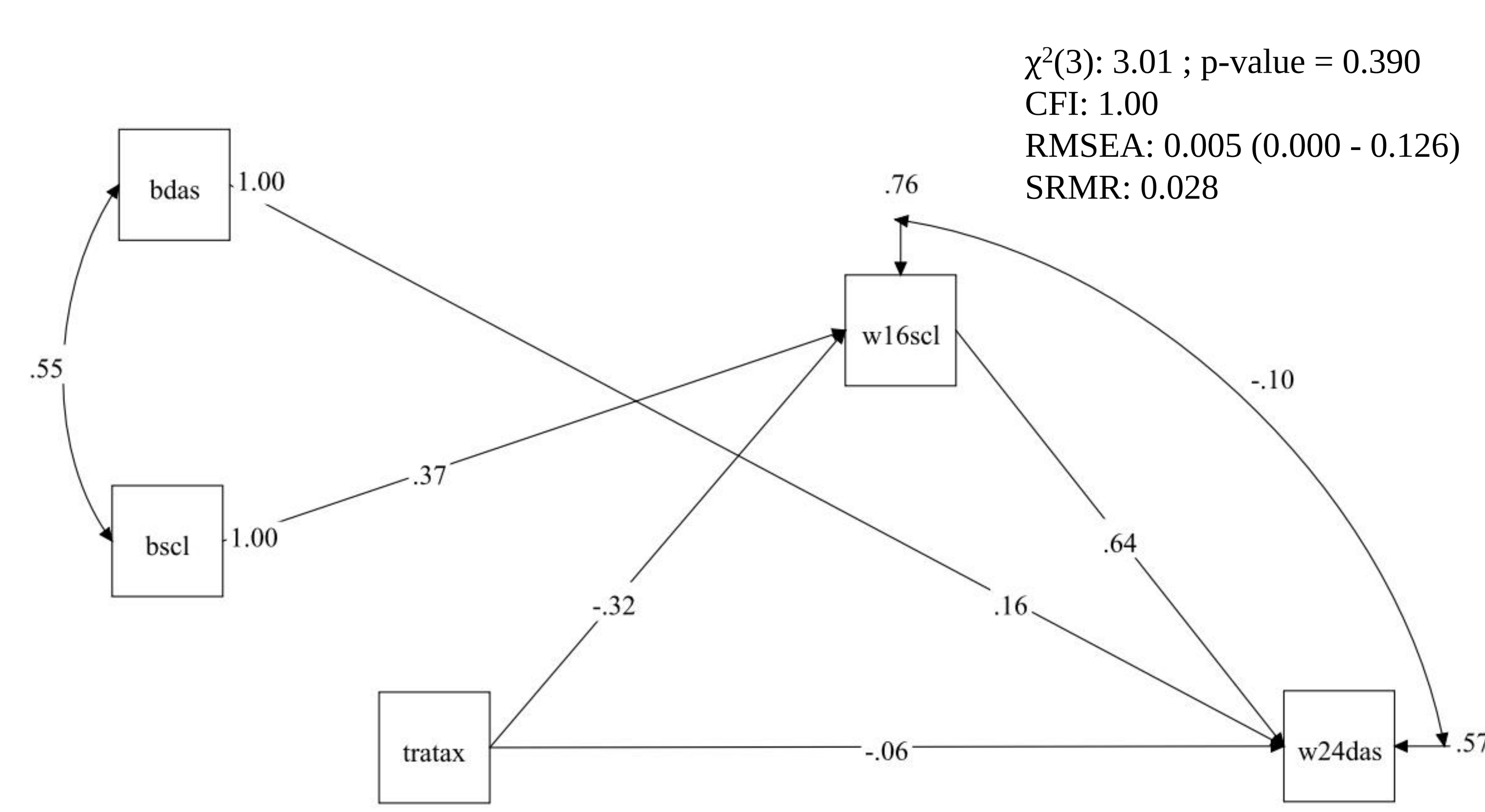
Expanded mediation model

Figure 2. Extended mediation model



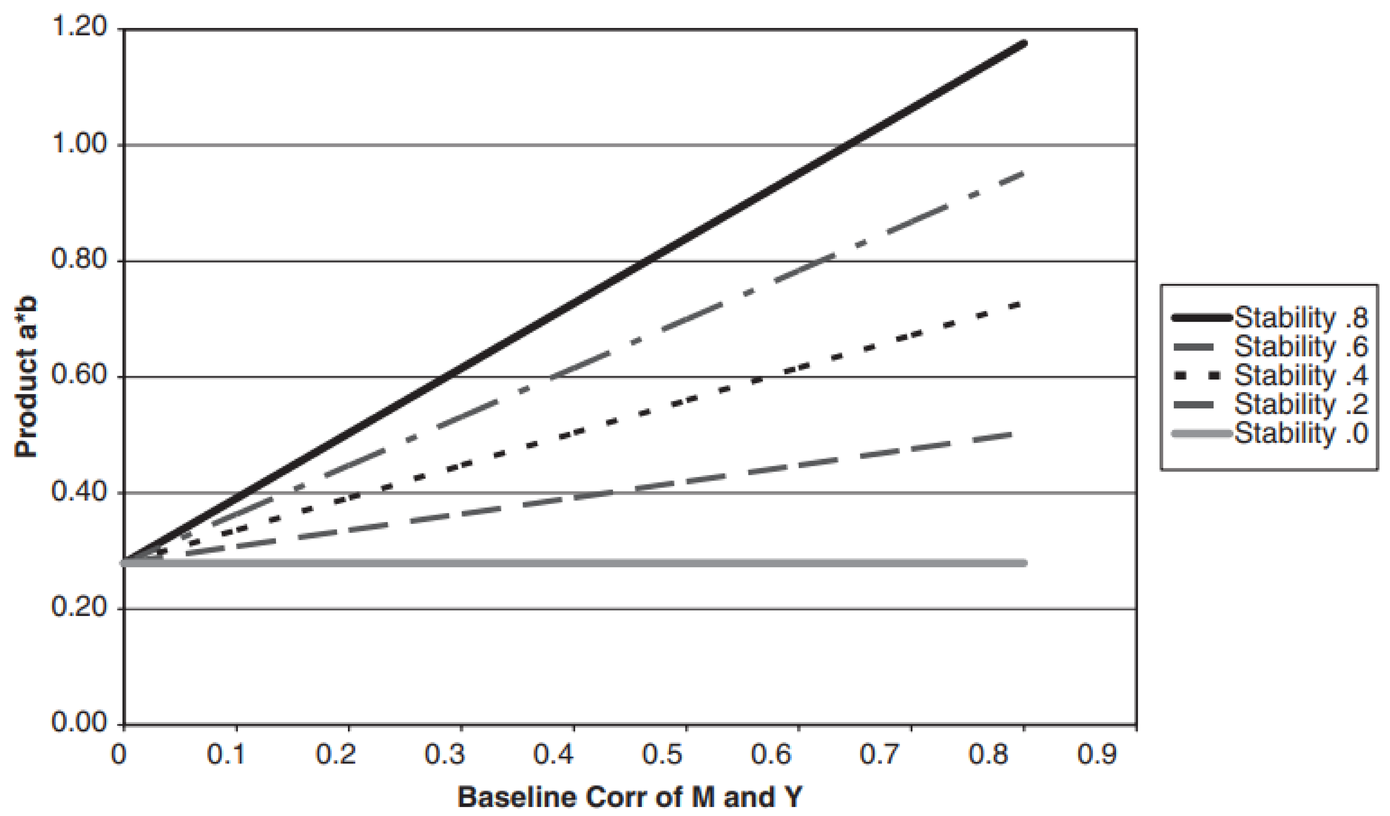
Empirical Identification

Figure 3. Extended mediation model applied on real experimental data



By having the baseline mediator variable affect only the subsequent mediator and the baseline outcome only the dependent variable, a previously theoretically unidentified confounder of mediated effects can be estimated, along with its standard error and significance test. The potential source of bias is the correlation between the residuals of the mediator and the residuals of the dependent variable. In the classic mediation model researchers must assume this confounder being zero.

Figure 4. Indirect effect bias by stability level



Shrout, Keyes and Ornstein (2011) presented data showing how when both the mediator and outcome variable have a moderate stability and correlation at baseline, the bias introduced by the correlation between residuals can be substantial and introduce important bias in estimates of indirect effects.

Future directions

Coffman (2011) wrote about correcting for selection bias and confounding when subjects are not randomly assigned to levels of the mediator using propensity scores, assuming that all confounders are identified. Future simulation studies should explore if this model is able control for confounding on the mediated effect without the need of propensity scores. In addition, this model assumes that T is uncorrelated with M and Y at baseline. If T is correlated with baseline M or Y, model fit will suffer, rendering the model uninterpretable. Future studies should explore the application of propensity score methods to control for this additional source of confounding, allowing for proper fit of the expanded mediation model and provide unbiased and interpretable estimates of *a X b*.

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