Introduction to Mediation and Moderation Concepts and Methods
Tor Neilands, PhD
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Questions and Answers

1. Gilbert MacKenzie:
    a. Limitation is that M=1variable in your example So …?

        Response: The traditional X->M->Y mediation model is likely the most common model fitted in applications with actual data. It is also the simplest to present as a starting point when introducing the concept of mediation and the causal steps method. However, as illustrated later in the presentation when discussing structural equation modeling (SEM) and also post-exposure confounding, multiple mediator models can be estimated by SEM and specific causal mediation models.

    b. But what about Goodness of fit.? When I see these complex diagrams I want remove arrows and simplify - what about information criteria?

        Response: Yes, when using the SEM method to fit mediation models, it is useful to examine global model fit statistics. It's worth noting that the classical X->M->Y sequential mediation model is fully saturated with zero degrees of freedom, so SEM global model fit tests aren't applicable because the model will reproduce the sample covariance matrix exactly. However, for multiple mediator models, evaluating goodness of fit can be helpful.

        As was discussed in the verbal response to the question about model simplification, while there are some limitations inherent in modifying a pre-specified SEM post-hoc, removal of non-significant pathways appears to be a largely accepted practice to improve global model fit and to improve the efficiency of the remaining parameter estimates. In the longitudinal SEM example I showed, we took a similar approach in imposing equivalence constraints on various parameters (e.g., setting equal the autoregressive pathways from earlier time points to later time points for the mediating and outcome variables).

        Information criteria can be useful for SEMs estimated via maximum likelihood in order to compare nested or non-nested models and could be used to evaluate whether to retain vs. remove certain paths from a given SEM.

    c. Casual inference averages given observational data where the mediated effects are built in - this is flawed.?

Response: As was discussed during the verbal Q&A, causal inference methods do have limitations and assumptions. For instance, as Dr. MacKenzie pointed out in the verbal Q&A, sometimes a treatment may not be randomly assigned and/or cannot be randomly assignable. In such settings, identification and control of confounders is especially important. Unobserved confounding may still introduce bias. The causal mediation literature presents methods to assess the amount and impact of unobserved confounding on mediation analysis results.

It is also worth noting that while causal mediation methods make certain assumptions, most if not all of those same assumptions apply to alternative mediation assessment methods. Researchers are not required to use causal mediation methods. As an example, the talk covered SEM as a powerful and highly flexible method for assessing mediation in models ranging from simple to highly complex. Moreover, other mediation approaches exist that do not rely explicitly on a causal inference framework. I did not have time to cover those methods in this presentation. Examples include Andrew Hayes's PROCESS method (Hayes, 2022) (https://www.processmacro.org/index.html) and the KHB method (Breen, Karlson, & Holm, 2013). The latter method was developed primarily for comparing coefficients between nested models with non-continuous outcomes, but a byproduct of the approach is that it yields indirect effect estimates. The KHB method is implemented in the Stata community-contributed command -khb- (Kohler, Karlson, & Holm, 2011).

However, causal mediation methods do have some attractive features, including the option of assessing models with non-continuous M and/or Y variables and evaluating exposure-mediator interactions. Another exciting development is the uniting of the benefits of SEM (e.g., latent variables) with causal mediation. Some of these developments are supported in the specialized latent variable modeling program M*plus*. I did not have time to discuss mediation assessment options available in M*plus*; those are described in a textbook (Muthen, Muthen, & Asparouhov, 2016)and several articles (Muthén, 2011; Muthén & Asparouhov, 2015).

During the Q&A session of the talk, we also discussed mediation in a survival analysis context. Dr. Tyler Vanderweele and his colleagues have done work in this area via a causal mediation framework and has published articles on this subtopic and has shared a SAS macro for performing mediation analyses with survival data (Lin, Young, Logan, & VanderWeele, 2017; Valeri & VanderWeele, 2015).

Finally, I'd like to comment that my general impression is that the current state of causal mediation modeling is that methodologists have been developing these approaches and sometimes publishing software code for specific mediation contexts and models, but there is not yet a general purpose global software solution that can fit most causal mediation models as there is with SEM as a general purpose non-causally-oriented method that can fit a very wide range of mediation models. In my opinion, one of the next frontiers in causal mediation methods research will be development of such general software solutions, which will be challenging due to the complexity of causal mediation methods.

2. Lewis Lee:
    a. Regarding model fit indices, if CFI shows good (i.e., >.90) but TLI doesn't (< .90), can I report only CFI?

        Response: The CFI (Comparative Fit Index) is a descriptive index of approximate global model for SEMs. My opinion is that one would usually want to report one of these SEM global model fit statistics, but not both. That is because both TLI and CFI are very similar and belong to the same broad class of SEM fit statistics: they are considered incremental fit indices (IFIs) that compare the fitted model to a baseline (also known as a null or independence) model in which all observed variables are uncorrelated. The TLI and CFI formulae are quite similar. I prefer CFI because it is normed to have values between 0 and 1 and my impression is that it has been more extensively studied in statistical simulations than TLI.

        In addition to CFI, I typically report the standardized root mean square residual (SRMR) and root mean square error of approximation (RMSEA) approximate fit statistics for SEM following the guidelines and thresholds recommended by Hu and Bentler in their seminal paper on this topic (Hu & Bentler, 1999). That publication recommends either SRMR ≤ .08 and RMSEA ≤ .06 OR SRMR ≤ .08 and CFI ≥ .95 as indicating satisfactory approximate model-data fit for SEMs.

3. Xiaoying Yu:
    a. If possible, how to assess the potential role (moderator, confounder and mediator) or the mixed roles for one variable Z between the relationship of two variables (X,Y)?
    b. Just further clarification on the question: If possible, how to assess the potential role (moderator, confounder and mediator) or the mixed roles for one variable Z

between the relationship of two variables (X,Y) SIMUTANUOUSLY, not by separate analysis?

Response: An advantage of the causal mediation approach covered in today's presentation is that one can simultaneously evaluate whether a variable is a moderator and a mediator. As to whether a variable is a confounder, one could evaluate whether it affects X and Y as shown in the diagram on this page: https://en.wikipedia.org/wiki/Confounding. If it does, it could be considered a confounder. I think the evaluation of confounding by a variable Z would need to be undertaken separately from the evaluation of whether Z is a mediator and/or moderator – I'm unaware of a unified method that would enable one to assess all three potential roles for a given variable in the same analysis.

4. Benjamin J Seligman:
   a. Is there guidance on using asymmetrically distributed variables as moderators?

      Response: I'm not sure whether this question is referring to categorical moderators or continuous moderators. For categorical moderators, maximum power for testing hypotheses should be achieved when the categories have equivalent numbers. I'm not sure how the distribution of a continuous moderator would affect an analysis, but suspect that an asymmetrically distributed continuous variable might have reduced power in moderation analyses due to reduced variability (relative to an otherwise equivalent symmetrically distributed variable). So, while you can certainly use asymmetrically distributed variables as moderators, I would say they are probably not going to be ideal moderators. Of course, oftentimes our data are not ideal and we make the best of what we have available.

5. Michelle Nakphong:
   a. Could you comment on/provide some resources about power and sample size considerations for mediation analyses?

      Response: There are a number of sample size articles and calculators available for mediation models. These include several freely-available R packages, e.g., https://cran.r-project.org/web/packages/powerMediation/powerMediation.pdf and my colleague Eric Vittinghoff's R package described in and linked from our 2015 publication in Prevention Science (Vittinghoff & Neilands, 2015). Some commercial power calculation programs such as NCSS PASS and GPower also support sample size and power calculation for mediation assessment. Fritz and

Mackinnon have published a table showing estimated sample sizes needed to achieve 80% power for various mediation assessment methods (Fritz & Mackinnon, 2007). David Kenny has also written an online web-based power calculator for mediation analysis (https://davidakenny.shinyapps.io/MedPower/).

Some calculators only consider the classical scenario in which both the mediator M and the outcome Y are assumed to be continuous and normally distributed and fitted with linear regression models whereas other calculators allow consideration of other types of mediators and outcomes. Most if not all mediation power calculators assume the traditional X->M->Y sequential mediation model; power for more complex mediation models may need to be estimated via Monte Carlo simulation.

References

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