Commentary: Causal Effects in Mediation Modeling: An Introduction with Applications to Latent Variables

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A commentary on

Causal Effects in Mediation Modeling: An Introduction with Applications to Latent Variables

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Causal mediation\(^1\) is an increasingly popular analysis, as recently described by Muthén and Asparouhov (2015, M&A)\(^2\). We suggest a simplified notation for causal mediation effects, \(i_T/i_P=M\&A\) and \(d_T/d_P\), provide a graphical view of potential outcomes (PO) and expand the M&A approach by using VanderWeele's (2014) mediation decomposition.

An intuitive way to label and see causal in/direct effects is to directly display POs, as in Figure 1 below. POs are values that could be observed, but have not been realized (yet). They reveal themselves partially once nature or researchers assign people to specific experimental conditions, or when people make choices. POs are useful in defining causal total effects (TE), as differences between the same individual’s (i) two POs, \(Y_{11} - Y_{10}\), had the person been treated (subscript 1), and alternatively (but simultaneously) not treated (0); evidently, in our reality one of these has to be “contrary-to-fact” (CF).

The indirect effect of X on Y through a mediator M is the part of the total effect that "flows through" M, or the contribution of the path X->M->Y to the observed association between X and Y, which is an open path because causal association flows through it (Elwert, 2013). The key problem in intuitively grasping causal in/direct effects is the “nesting” of the POs due to the double role of the mediator as a cause and an effect\(^1\): the PO "Y if X was set to x," or \(Y_x\), can be combined with "Y if M was set to m," or \(Y_m\) (we suggest using a superscript for scenarios involving M). So \(*Y_{11}M_0\) for example, labeled \(Y(1, M(0))\) in M&A, is the PO of the outcome Y if a person was treated (\(Y_1\)), but his/her mediator took on the value had s/he would belonged to the opposite (control) condition \((M_0)\). This PO is clearly contrary-to-fact (CF), never observable, a “cross-worlds” quantity (Lok, 2016), hence our * sign. \(Y_0\) and \(Y_1\) are in principle realizable, only one of them at a time for the same person, however.

The label “causal” mediation reflects more than the expansion of the original Baron and Kenny model to allow for X-by-M interaction, and does not suddenly make any three-variable model causal in the profound sense. Causal mediation relies on meeting other assumptions, like the no-confounder assumption of M and Y, and would require causal investigations like those afforded by Direct Acyclic Graphs (DAGs, Greenland et al., 1999).

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\(^2\)Another dominant causal mediation “schools” are led by the Imai (Imai et al., 2010) and Pearl (Pearl, 2001) teams, first centered on R and Stata implementations, the latter more theoretical and non-parametrical. They differ also in terms of formulating the assumptions for identification of the causal in/direct effects.

\(^3\)Pearl (2013) calls them nested counterfactuals; the key insight Sewall Wright foresaw when proposing the path analytic method may have been that the change in Y in relation to the change in X (the slope SY/SX), traced on the path through an intermediary M, is linked to the slopes SY/SX and SY/SM following the composite function chain rule of derivatives: \(\delta Y/\delta M \cdot \delta M/\delta X\), which mirrors the Baron and Kenny \(i = a \cdot b\). Adding the contributions of all such X-to-Y open paths yields the model predicted association between X and Y (see the “tracing rule,” Looslin, 2004).
The four key POs involved in understanding causal in/direct effects are shown in Figure 1. The total effect is decomposable into direct and indirect causal effects, possibly in two ways, through one of two fully contrary-to-fact POs: *Y_1^0* or *Y_0^1*.

Both decompositions of TE can be obtained by adding and subtracting a fully CF intermediary term; e.g., through *Y_0^1*:

\[ TE = Y_1 - Y_0 = (Y_1 - Y_0) + (Y_1 - Y_0) = \text{d}_T + \text{dp} \]  

Intuitively, one can see that the two vertical arrows are direct effects, because they capture the "change" in Y (in the PO world), marked by subscript/superscript changes: when "changing" only X, i.e., while (un-naturally) holding the mediator at a "constant" PO-value. The causal pure direct effect d_p is often referred to as natural (or pure natural direct effect, PNDE, in M&A), because the mediator takes on the same value under the control condition, which would be the “natural” course of action without any change in nature.

Similarly, the two horizontal arrows are indirect effects, because they are the result of "changing" only M, while keeping X constant (at 0, or 1)^4. The "upper" indirect effect is called

\[ \text{d}_T = \text{dp} + \text{INT}_{\text{Med}} \quad \text{and} \quad \text{i}_T = \text{ip}_B + \text{INT}_{\text{Med}} \]  

where INT_{\text{Med}} is the mediated interaction component^5, which is the product of the interaction estimate and the X→M linear effect, \( \beta_{X \rightarrow M} \), a, labeled \( \gamma_{11} \cdot \beta_3 \) in M&A, see their Equations (5) and (9); INT_{\text{Med}} is non-zero when X impacts M, and X and M interact in how they impact Y.

Because the Mplus software code in M&A for computing causal in/direct effects did not estimate the effects proposed by VanderWeele's "decomposition" (mediated interaction, controlled direct effect, proportion attributable to interaction, and portion eliminated), we expand the Mplus code for continuous M and Y to estimate them (see the online appendix at https://bit.ly/pos_frontiers); we present an expanded VanderWeele SAS code too, which estimates the Mplus additional effects: pure direct, total indirect and total direct.

To illustrate, we estimated effects from a weight-loss randomized intervention data (SisterTalk Hartford, Burleson et al., 2008; de-identified data for replication available in appendix), which was meant to improve food habits and consequently reduce BMI in African-American women; effects are shown in Equation (3) (following VanderWeele's Figure 4, 2013, which is an expanded online version of the published (VanderWeele, 2014); * signals statistically significant at \( p < 0.05 \), NS signifies non-significant):

\[
\begin{align*}
\text{d}_T & = \text{dp} + \text{INT}_{\text{Med}} = \frac{m_{\text{CDE}}}{0.507^* (76\%)} + \frac{m_{\text{INT}_{\text{Med}}}}{0.021^{NS} (-3\%)} = -0.495^* (75\%) \\
\text{i}_T & = \text{ip}_B + \text{INT}_{\text{Med}} = \frac{\text{+ INT}_{\text{Med}}}{0.012^{NS} (-2\%)} = -0.168^* (25\%) \\
\text{d}_T & = -0.474^* (71\%) \\
\text{i}_T & = -0.189^* (29\%) \\
\text{ip}_B & = -0.189^* (29%) \\
\end{align*}
\]

where INT_{\text{Med}} is the mediated interaction, BK is the “Baron and Kenny” causal indirect effect, m_{\text{CDE}} is the controlled direct effect, m_{\text{INT}_{\text{Ref}}}, reference interaction, with superscript m signaling that those effects depend on what value m the analyst decided to estimate them at.

The fact that there is possibly more than one indirect (and hence direct) effect to estimate follows from the interaction of X and M in causing Y, which makes the effect of M on Y vary with X (or the effect of X on Y vary with M).

^4The fact that there is possibly more than one indirect (and hence direct) effect to estimate follows from the interaction of X and M in causing Y, which makes the effect of M on Y vary with X (or the effect of X on Y vary with M).
The total effect $TE$ was $-0.66$ BMI units (approx. $-3.9$ lbs. for an average 64 inch woman). The mediated interaction effect $INT_{Med}$ is about 3% of the TE, and statistically non-significant, hence statistically $I_{Med}^{stat} = IP_{BK}^{stat}$ and $d_{IP}^{stat} = d_{BK}$ ("stat." signals statistical, not mathematical, equality), so one can report the classic $BK$: the weight loss achieved through improving one's food habits is about 25% of the total effect, while the residual direct effect is about 75% of it.

While POs are central to “causal” mediation, visually “seeing” them is challenging, yet, when achieved, it helps uncover the mechanisms behind causal direct and indirect effect estimation. Intuitive graphical displays could aid in visualizing some assumptions, many of which refer to relations between POs, and not their observed cousins (e.g., ignorability, or unconfoundedness, Imai et al., 2010); such assumptions ensure identifiability of in/direct causal effects.

We hope that the simplified notation and a visual display of how causal in/direct effects emerge from a mix of the POs of the mediator and the final outcome can contribute to a more intuitive understanding and reporting of causal mediation, as presented in the seminal paper we commented on. The notational bridge and cross-pollination of software syntaxes we suggested should facilitate such an improved understanding.

**AUTHOR CONTRIBUTIONS**

ENC has developed the idea, FT has verified the claims, expanded, and revised the manuscript extensively, JF has worked on the theoretical and design portion of the original study and has revised and edited the manuscript.

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**REFERENCES**

Baron, R. M., and Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research: conceptual, strategic, and statistical considerations. J. Pers. Soc. Psychol. 51, 1173. doi: 10.1037/0022-3514.51.6.1173

Burleson, J., Curry, L., Dauser-Forrest, D., Henderson, C., McKinney, M., Pelle, M. et al. (2008). "Testing the Social Action Theory framework of a faith-based weight control program collaboratively translated with African-American and Black Women: SisterTalk Hartford," in Paper Presented at the Annual Meeting of North American Primary Care Research Group (Rio Grande).

Elwert, F. (2013). “Graphical causal models,” in Handbook of Causal Analysis for Social Research, ed S. L. Morgan (New York, NY: Springer), 245–273.

Greenland, S., Robins, J. M., and Pearl, J. (1999). Confounding and collapsibility in causal inference. Stat. Sci. 14, 29–46.

Imai, K., Keele, L., and Tingley, D. (2010). A general approach to causal mediation analysis. Psychol. Methods 15, 309–334. doi: 10.1037/a0020761

Loeblin, J. C. (2004). Latent Variable Models: An introduction to Factor, Path, and Structural Equation Analysis. Mahwah, NJ: Lawrence Erlbaum.

Lok, J. J. (2016). Defining and estimating causal direct and indirect effects when setting the mediator to specific values is not feasible. Stat. Med. 35, 4008–4020. doi: 10.1002/sim.6990

Muthen, B., and Asparouhov, T. (2015). Causal effects in mediation modeling: an introduction with applications to latent variables.

Pearl, J. (2001). “Direct and indirect effects” in Proceedings of the Seventeenth Conference on Uncertainty in Artificial Intelligence. Available online at: ftp://ftp.cs.ucla.edu/pub/stat_ser/R273-U.pdf

Pearl, J. (2013). Structural counterfactuals: a brief introduction. Cogn. Sci. 37, 977–985. doi: 10.1111/cogs.12065

VanderWeele, T. J. (2013). A Unification of Mediation and Interaction. Harvard University Biostatistics. Working Paper Series. Available online at: http://biostats.bepress.com/harvardbiostat/paper164

VanderWeele, T. J. (2014). A unification of mediation and interaction: a 4-way decomposition. Epidemiology 25, 749–761. doi: 10.1097/EDE.0000000000000121

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