Australasian Marketing Journal ■■ (2017) ■■–■■

Contents lists available at ScienceDirect

Australasian Marketing Journal

journal homepage: www.elsevier.com/locate/amj

Commentary

The analysis of mechanisms and their contingencies: PROCESS versus structural equation modeling

Andrew F. Hayes *, Amanda K. Montoya, Nicholas J. Rockwood

Department of Psychology, The Ohio State University, Columbus, Ohio, USA

ARTICLE INFO

Article history:
Available online

Marketing researchers and those who study organizational or consumer behavior strive to understand how marketing and other organizational effects operate, meaning the underlying cognitive, social, and biological processes that intervene between a stimulus (e.g., a particular kind of packaging or promotion, or the management style of a leader) and a response (e.g., the evaluation of a product, a decision or timing to purchase, or employee turnover at a company). Mediation analysis is a popular statistical procedure for testing hypotheses about the *mechanisms* by which a causal effect operates. A mediation model contains at least one mediator variable *M* that is causally between *X* and *Y*, such that *X*'s effect on *Y* is transmitted through the joint causal effect of *X* on *M* which in turn affects *Y*. Fig. 1, panel A, depicts a mediation model with two mediators. Some examples found in the pages of *Australasian Marketing Journal* include Kongarchapatara and Shannon (2016), Baxter and Kleinaltenkamp (2015), and Schiele and Vos (2015). Such models are commonplace in the empirical literature.

Less common but growing in frequency are mediation models that allow for *moderation* of a mechanism, what Hayes (2013) calls a *conditional process model*. Fig. 1, panels B, C, and D, represent a few conditional process models, also known as *moderated mediation* models. Panel A is a *first stage* conditional process model that allows the effect of *X* on *M* in a mediation model to depend on variable *W*. The moderator, *W*, could be anything that influences or changes the effect of *X* on *M*. For some examples, see Voola et al. (2012), White et al. (2016), Shen et al. (2016), and Zenker et al. (2017). But if the moderation operates on the second stage of a mediation process (i.e., on the effect of *M* on *Y*), as in Cassar and Briner (2011) and Dubois et al. (2016), the result is a *second stage* conditional process model, as in Fig. 1, panel C. If the same moderator influences the relationship between *X* and *M* and *M* and *Y* (Fig. 1, panel D), this is a *first and second stage* conditional process model. Examples include Shenu-Fen et al. (2012) and Etkin and Sela (2016). These represent only three of the many ways that mediation and moderation can be integrated into a unified model.

Each of the models depicted in Fig. 1 looks like a path diagram, with variables connected with unidirectional arrows. Such diagrams, for most researchers, bring to mind structural equation modeling (SEM) as the proper analytical strategy. Yet most of the guidance offered by methodologists in the last 10 years or so on how to test the contingencies of mechanisms (i.e., whether "mediation is moderated") is framed in terms of ordinary regression-based path analysis principles (e.g., Edwards and Lambert, 2007; Fairchild and MacKinnon, 2009; Hayes, 2015; Muller et al., 2005; Preacher et al., 2007). Tools written for software frequently used by business and marketing researchers (such as SPSS and SAS) that do all the necessary computations have made applying these methods rather painless. The PROCESS macro introduced by Hayes (2013) has become especially popular in business and marketing (and many other fields as well), as evidenced by its appearance in a variety of business journals and research presented at academic conferences.

We frequently get questions about how PROCESS works, what it is doing, and what it can and cannot do.[1] One category of these questions involves the differences between what PROCESS does and what an SEM program does and if it matters whether one tests a mediation or conditional process model using PROCESS or SEM. Some of these questions are motivated by PROCESS users who have been told by reviewers or editors that they should or must use SEM, and they are not sure how to respond, or they wonder whether they have done something wrong. This short piece addresses these questions. Previous publications have discussed some of the issues we raise (Iacobucci et al., 2007; Pek and Hoyle, 2016), but without the focus on PROCESS that is unique to our treatment. We first briefly

* Corresponding author. Fax: +1 614 292 6798.
E-mail address: hayes.338@osu.edu (A.F. Hayes).

[1] The first author of this paper (Hayes) is the inventor of PROCESS. The other two authors are (at the moment this paper was drafted) Ph.D. students of Hayes working in his lab and regularly field questions from users of PROCESS.

http://dx.doi.org/10.1016/j.ausmj.2017.02.001

Please cite this article in press as: Andrew F. Hayes, Amanda K. Montoya, Nicholas J. Rockwood, Australasian Marketing Journal (2017), doi: 10.1016/j.ausmj.2017.02.001

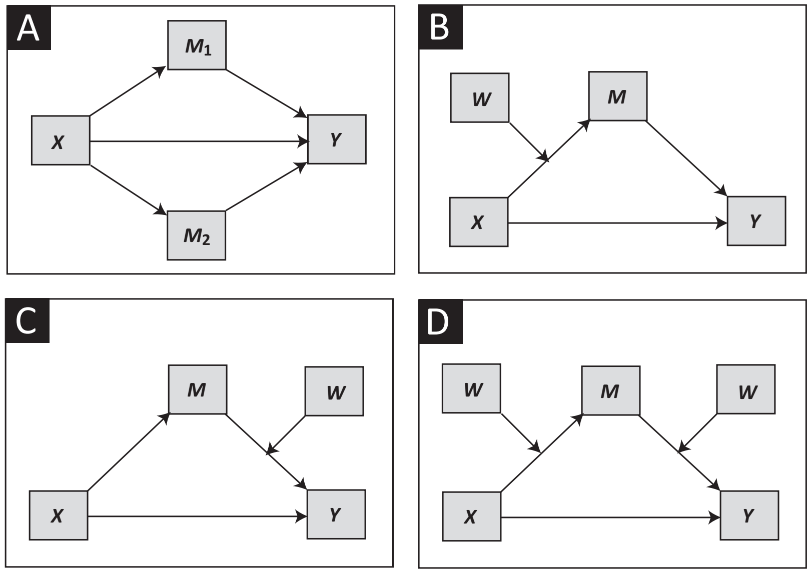

Fig. 1. A multiple mediator model (panel A) and three conditional process models (panels B, C, and D).

overview what PROCESS is and how it differs from what an SEM program does. We then show by way of example (though the lessons learned by this example generalize beyond it) that for an observed variable model (i.e., no latent variables), it makes little difference whether PROCESS or an SEM program is used. We then discuss some reasons why one might choose SEM over PROCESS.

1. What is PROCESS and how does it differ from SEM?

PROCESS is a computational tool — a "macro"—available for SPSS and SAS that simplifies the implementation of mediation, moderation, and conditional process analysis with observed (i.e., "manifest") variables. It was launched with the publication of Hayes (2013) and can be downloaded at no charge from www.processmacro.org. Based on a set of conceptual and statistical diagrams defined by a model number, the user chooses a model preprogrammed into PROCESS corresponding to the model he or she wants to estimate. Arguments are provided to the macro about what variables are serving which roles in the model (i.e., independent variable, dependent variable, mediator, moderator, covariate), and PROCESS estimates all the path coefficients, standard errors, *t*- and *p*-values, confidence intervals, and various other statistics.

Except in models that contain only a moderation component, every model that PROCESS estimates requires at least two regression equations. PROCESS uses ordinary least squares regression to estimate the parameters of each of the equations, a common practice in observed variable path analysis. For instance, the model in Fig. 1, panel A, requires three equations (one for each mediator M_1 and M_2, and one for Y), whereas the models in Fig. 1 panels B, C, and D each require only two regression equations (one for M and one for Y). PROCESS estimates each equation *separately*, meaning that the estimation of the regression parameters in one of the equations has no effect on the estimation of the parameters in any other equations defining the model. Regardless of how many equations are needed, once the PROCESS macro is activated, one line of SPSS or SAS code is all that is required to estimate the model, which makes it a very simple and user-friendly modeling system. SPSS users can also set up the model using a convenient point-and-click interface by installing an optional PROCESS dialog menu into SPSS.

PROCESS is not needed to estimate the parameters of the regression equations, as this can be done with any least squares regression program (such as SPSS's REGRESSION command or PROC REG in SAS) and the results will be identical. But in mediation and conditional process analysis, many important statistics useful for testing hypotheses, such as conditional indirect effects and the index of moderated mediation, require the combination of parameter estimates across two or more equations in the model. Furthermore, inference about these statistics is based on bootstrapping methods, given that many of these statistics have irregular sampling distributions, making inference using ordinary methods problematic (Hayes, 2013; Shrout and Bolger, 2002). PROCESS does all this behind the scenes and generates output that would otherwise require considerable effort and programming skill to implement.

Any SEM program can do path analysis with observed variables as PROCESS does, although most require more code (and the skill to write that code) than what is required to generate many of the statistics that PROCESS produces automatically. Furthermore, not all SEM programs can generate all of the statistics PROCESS calculates or implement bootstrapping in a way that facilitates inference using those statistics. Although Pek and Hoyle (2016) argue that regression based approaches are not as easily implemented as SEM, we believe that with PROCESS, the opposite is true. Most researchers will find PROCESS far easier to use than any SEM program.

Other than ease of use, one of the more important differences between PROCESS and SEM programs is that SEM solves the entire system of equations simultaneously through iteration, typically using maximum likelihood (ML), rather than estimating the parameters of each equation independently. This involves finding an initial set of parameter estimates for every variable in every equation defining the model and then tweaking them simultaneously at each iteration after measuring the correspondence between the covariance matrix of the variables in the model and the covariance matrix implied by the model given the estimates derived. The estimation stops when further modification to the estimates does not improve the correspondence more than as required by the convergence criterion.

Because SEM estimates the components of the model simultaneously, Pek and Hoyle (2016) recommend SEM and suggested that the piece-wise nature of estimation with regression encourages

Please cite this article in press as: Andrew F. Hayes, Amanda K. Montoya, Nicholas J. Rockwood, Australasian Marketing Journal (2017), doi: 10.1016/j.ausmj.2017.02.001