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Commentary

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

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ABSTRACT

Marketing, consumer, and organizational behavior researchers interested in studying the mechanisms by which effects operate and the conditions that enhance or inhibit such effects often rely on statistical mediation and conditional process analysis (also known as the analysis of "moderated mediation"). Model estimation is typically undertaken with ordinary least squares regression-based path analysis, such as implemented in the popular PROCESS macro for SPSS and SAS (Hayes, 2013), or using a structural equation modeling program. In this paper we answer a few frequently-asked questions about the difference between PROCESS and structural equation modeling and show by way of example that, for observed variable models, the choice of which to use is inconsequential, as the results are largely identical. We end by discussing considerations to ponder when making the choice between PROCESS and structural equation modeling.

CHINESE ABSTRACT

营销、消费者和组织行为研究人员对研究这种影响经营的机制非常感兴趣，增强或抑制这种影响的条件通常依赖于统计调节和在一定条件下的处理分析（也叫做分析"适度调节"）。模型评估通常采用普通最小乘法基于回归的路径分析（例如，在 SPSS 和 SAS 深受青睐的 PROCESS 宏中实现[Hayes, 2013]）或采用结构方程模型方案。本文回答了一些有关 PROCESS 和结构方程模型之间区别的常见问题，并举例说明，对于观察的变量模型，选择使用哪种模型都无关紧要，因为其结果都大同小异。本文结尾讨论了在PROCESS和结构方程模型之间进行选择时应考虑哪些因素。

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

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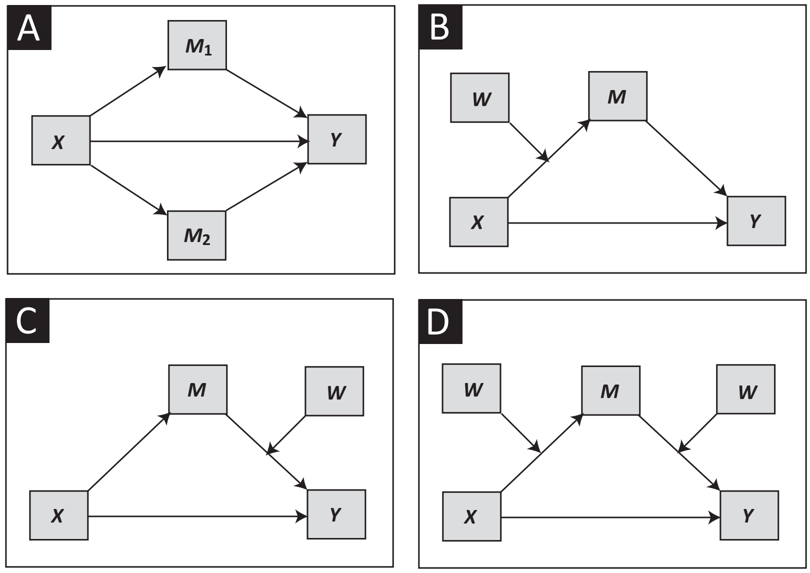

Fig. 1. A multiple mediator model (panel A) and three conditional process models (panels B, C, and D).

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 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.

[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.

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 researchers to think about mediation as a *procedure* rather than as a *model.* To be sure, users of the approach introduced to social scientists by Baron and Kenny (1986) overly focus on the components of the model rather than the model as a whole. But the popularity of this procedure has been waning over the last few years. The more modern focus on the indirect effect and other statistics in conditional process analysis that integrate across the pieces (as PROCESS does) forces the analyst to contemplate the model as a whole rather than just its pieces. We believe most users of PROCESS and users of SEM are thinking similarly and interact with the output of their chosen method in much the same way.

2. Does the choice of PROCESS rather than SEM matter?

Does it matter whether one uses PROCESS as opposed to an SEM program? Specifically, will one's results be influenced by whether PROCESS or an SEM program is used? Given that SEM and PROCESS are based on different estimation methods and theory, some differences can be expected. However, for models of observed variables (i.e., nothing latent), differences in results tend to be trivial, and rarely will the substantive conclusions a researcher arrives at be influenced by the decision to use PROCESS rather than SEM. Here we illustrate by example, recognizing that one demonstration of a phenomenon does not equate to a general proof.

An example of the similarity in results between PROCESS and an SEM program is provided in Hayes (2013) for a multiple mediator model (such as in Fig. 1, panel A). In this demonstration, we show this similarity with a more complex conditional process model. The data come from Cole et al. (2008), who examined the role of affect in the link between dysfunctional team behavior and team performance. The variables in the model are measured at the team level from 60 teams working at an automobile parts manufacturing facility. The variables include dysfunctional team behavior (X), team performance (Y), negative emotional tone of the team work environment (M), and how emotionally expressive the team is from the perspective of the supervisor (W), all of which are continuous dimensions and based on aggregates (average or sum scores) of various questions the employees or their supervisor were asked. Three dummy variables coding manufacturing parts division (4 divisions) are also available and used as covariates (U_1, U_2, and U_3) in the analysis.

In this model, dysfunctional team behavior is estimated as affecting team performance through its effect on the negativity of the team work climate, which in turn lowers performance. But the relationship between the negativity of the work environment and performance is estimated as linearly moderated by the expressivity of the team. Thus, this is a second stage conditional process model as in Fig. 1, panel C. The mechanism linking X to Y through M is allowed to be moderated in the second stage (i.e., the $M \rightarrow Y$ path) of the process. The model also includes a direct effect from dysfunctional team behavior to performance. For details on the theory and existing research underlying this model, see Cole et al. (2008).

This model is estimated with two equations:

$$\hat{M} = i_M + a_1X + a_2U_1 + a_3U_2 + a_4U_3 \tag{1}$$

$$\hat{Y} = i_Y + c'X + b_1M + b_2W + b_3MW + b_4U_1 + b_5U_2 + b_6U_3 \tag{2}$$

The index of moderated mediation, used for inference about whether the indirect effect of X on Y through M is moderated by W, is a_1b_3, with a bootstrap confidence interval used for inference (see Hayes, 2015). With evidence of moderation of the indirect effect, this moderation can be probed by estimating the conditional indirect effect of X at various values of W using the function $a_1(b_1 + b_3W)$, substituting values of W into this function once the model coefficients are estimated, and a bootstrap confidence interval used for inference (Edwards and Lambert, 2007; Hayes, 2013; Preacher et al., 2007).

This model was estimated using PROCESS version 2.16 and Mplus version 6. Mplus is a widely-used and versatile SEM program. As noted earlier, PROCESS estimates equations 1 and 2 separately using OLS regression while bootstrapping the sampling distribution of all parameter estimates, bringing them together across equations as needed for computation of conditional indirect effects, the index of moderated mediation, and bootstrap confidence intervals for these statistics. Mplus estimates the coefficients simultaneously and iteratively using maximum likelihood (the default, which we used). The MODEL CONSTRAINT command in Mplus allows for computation of the index of moderated mediation and conditional indirect effects using estimates from each equation, and the BOOTSTRAP option generates bootstrap confidence intervals. Mplus code for this illustration can be found in an online supplement available through afhayes.com or processmacro.org.

The results are displayed in Table 1. The bolded top entry in each cell is the point estimate, and the middle entry is the estimated standard error. As can be seen, the point estimates of model parameters, conditional indirect effects, and the index of moderated mediation are largely identical, with a few discrepancies at the third decimal place. Clearly, whether one uses separate OLS regression equations or an SEM program to estimate the coefficients makes no difference even in a small sample such as this. There are differences in the standard errors, but these are expected, as the underlying statistical theory of OLS versus ML sampling variance estimation is different and relies on different assumptions. There are also some discrepancies in the bootstrap confidence intervals for the conditional indirect effects and index of moderated mediation. But this has nothing to do with the smaller standard errors from SEM, as standard errors are not used in the construction of these bootstrap confidence intervals. These interval estimates are based on 10,000 bootstrap samples randomly constructed, and the 10,000 generated by PROCESS are, of course, not the same random samples generated by Mplus. Regardless, substantively, the results are the same, with evidence that the indirect effect varies linearly with the moderator (the index of moderated mediation), and the conditional indirect effect definitively different from zero among

Table 1
Path coefficients, standard errors, conditional indirect effects, and index of moderated mediation (with percentile bootstrap confidence intervals) for the second stage conditional process model in Fig. 1C, estimated using PROCESS and Mplus with the data from Cole et al. (2008).

		Negative tone of the work climate (M)		Team performance (Y)	
		PROCESS	Mplus	PROCESS	Mplus
Constant	Coeff	**–0.206**	**–0.206**	**–0.175**	**–0.177**
	s.e. ($n = 60$)	0.131	0.125	0.131	0.121
	s.e. ($n = 180$)	0.073	0.072	0.072	0.070
Dysfunctional behavior (X)	Coeff	**0.610**	**0.611**	**0.373**	**0.372**
	s.e. ($n = 60$)	0.167	0.160	0.181	0.169
	s.e. ($n = 180$)	0.093	0.092	0.099	0.097
Negative tone of the work climate (M)	Coeff	–	–	**–0.489**	**–0.489**
	s.e. ($n = 60$)			0.138	0.128
	s.e. ($n = 180$)			0.076	0.074
Team expressiveness (W)	Coeff	–	–	**-0.022**	**-0.022**
	s.e. ($n = 60$)			0.118	0.110
	s.e. ($n = 180$)			0.065	0.063
$M \times W$	Coeff	–	–	**–0.450**	–0.**450**
	s.e. ($n = 60$)			0.245	0.228
	s.e. ($n = 180$)			0.135	0.132
Division1 (U_1)	Coeff	**0.349**	**0.348**	**0.182**	**0.182**
	s.e. ($n = 60$)	0.172	0.164	0.172	0.160
	s.e. ($n = 180$)	0.096	0.095	0.095	0.092
Division 2 (U_2)	Coeff	**0.295**	**0.296**	**0.084**	**0.085**
	s.e. ($n = 60$)	0.212	0.203	0.210	0.195
	s.e. ($n = 180$)	0.119	0.117	0.115	0.113
Division 3 (U_3)	Coeff	**0.251**	**0.251**	**0.282**	**0.283**
	s.e. ($n = 60$)	0.166	0.159	0.165	0.153
	s.e. ($n = 180$)	0.093	0.092	0.091	0.089

		PROCESS	Mplus
Index of moderated mediation	Value	**–0.274**	**–0.275**
	95% CI ($n = 60$)	–0.705, –0.025	–0.704, –0.022
	95% CI ($n = 180$)	–0.469, –0.127	–0.480, –0.129
Conditional indirect effect at 1 SD below the sample mean of team expressiveness	Value	**–0.146**	**–0.147**
	95% CI ($n = 60$)	–0.439, 0.191	–0.425, 0.201
	95% CI ($n = 180$)	–0.288, 0.007	–0.292, 0.010
Conditional indirect effect at the sample mean of team expressiveness	Value	**–0.296**	**–0.297**
	95% CI ($n = 60$)	–0.564, –0.072	–0.560, –0.068
	95% CI ($n = 180$)	–0.431, –0.172	–0.435, –0.171
Conditional indirect effect at 1 SD above the sample mean of team expressiveness	Value	**–0.445**	**–0.446**
	95% CI ($n = 60$)	–0.783, –0.147	–0.783, –0.143
	95% CI ($n = 180$)	–0.619, –0.274	–0.630, –0.279

teams moderate to high in expressivity but not among teams low in expressivity.

If you think that the smaller standard errors when using SEM would favor simultaneous estimation using ML, think again. SEM is generally regarded as a large sample technique. The default estimation methods used by most SEM programs rely on large sample asymptotic theory. Although the performance of ML estimation in small samples is highly context dependent and depends on a variety of factors, in general, ML standard errors tend to be biased downward in small samples (Hoogland and Boomsma, 1998). So the apparent advantage of SEM evidenced by the smaller standard errors is likely illusory in this case and similar ones. Smaller standard errors are not better when they are wrong.[2]

To illustrate the effect of sample size on discrepancies in results, we repeated the analysis, pretending the sample size was 180 team members. This was accomplished by copying the data set twice, stacking each copy below the original in the data set, prior to estimation. The path coefficients don't change, but as can be seen in Table 1, the standard errors, of course, do. Most important, the discrepancies in standard errors between PROCESS and Mplus are now trivial. This example illustrates what we believe to be a general phenomenon. In small samples, there will be differences in the standard errors, but in bigger samples, it generally makes no difference whether you use ML-based SEM or PROCESS. The choice is yours, at least for observed variable models such as this. So we disagree with Iacobucci et al. (2007), who advocated the use of SEM rather than separate regressions in mediation analysis. We believe the interpretation of their findings fail to acknowledge the downward bias in ML standard errors when using SEM in smaller samples.

3. Considerations when making the choice

We do not intend to suggest above that there no advantages to using an SEM program rather than PROCESS when conducting a mediation or conditional process analysis. Hayes (2013, pp. 161–162) outlines some of these advantages, and here we elaborate on some of them while adding a few new ones. Our discussion of this topic is not exhaustive.

PROCESS is an observed-variable modeling tool that relies on OLS regression. One of the weaknesses of regression analysis is its susceptibility to bias in the estimation of effects due to random measurement error (see Darlington & Hayes, 2017, pp. 525–532). This weakness generalizes to regression-based mediation analysis. The extent of the bias, which can be positive or negative, depends

[2] But the differences in standard errors in this example are a bit larger than would be expected if small sample bias in ML standard errors was the only culprit. Many things can affect OLS and ML standard errors, and affect them differently, such as non-normality and heteroscedasticity.

on many factors, such as the complexity of the model, the degree of unreliability in measurement, and the correlation between the variables in the model (see Cole and Preacher, 2014, for a discussion). Given perfect reliability of measurement can rarely be assumed, this means that estimates of indirect and direct effects (conditional or unconditional) based on OLS regression probably are biased to some extent, in one direction or another.

Structural equation modeling can help manage the effects of measurement error, but it won't do so automatically. It only does so when the analyst combines a structural model (i.e., a model of the relationship between *latent* variables) with an explicit measurement model, with multiple indicators for each latent variable or using a single indicator with constraints in the model determined by an estimate of or guess about the reliability of the indicator (see e.g., Kline, 2016). Both these approaches can reduce bias in the estimation of effects in a mediation or conditional process analysis (see Cheung and Lau, 2015; Ledgerwood and Shrout, 2011). This cannot be done in PROCESS. No latent variables are allowed by PROCESS that haven't first been reduced to observed variable proxies (e.g., sum scores or averages of indicators), which make them, by definition, *observed* and not latent.

Researchers, reviewers, and editors who are aware of the problems produced by measurement error may question the legitimacy of results generated by PROCESS and insist that an SEM program with a combined measurement and structural model be used instead. Although this is a defensible position, three things are important to recognize. First, if that is the position one takes, it should be applied consistently, meaning such a critic should doubt the legitimacy of *any* analysis that can be expressed in the form of a linear regression model (even if not actually described as such in a manuscript). This would include regression analysis itself, analysis of variance and analysis of covariance, the independent group *t*-test, and even hypothesis tests involving the simple correlation between two variables. Though mediation analysis without a latent variable measurement model receives much criticism, all of these methods suffer from problems caused by random measurement error, to varying degrees and with various effects on inference. Our guess is that most who take this position have published their own research (or the work of others) using methods that are just as susceptible to measurement error-induced problems such as bias.

Second, structural equation modeling with a combined measurement and structural model is not a panacea to problems produced by imperfect reliability of measurement. Accounting properly for measurement error requires a proper model of that error, one that typically carries assumptions that may not be met. Furthermore, as Ledgerwood and Shrout (2011) discuss, biases in the estimation of one parameter can be offset by biases in another in the opposite direction, which is important given that indirect effects are the products of parameter estimates. In addition, standard errors in latent variable mediation analysis can actually be larger in some circumstances, even though bias in the estimation of the structural parameters is reduced compared to when using observed variable mediation analysis. So latent variable mediation analysis may be, at least in some circumstances, more *accurate* in the estimation of effects than observed variable analysis, but less *powerful* in detecting them.

Third, conditional process models have at least one interaction between variables. The proper estimation of interactions between latent variables remains highly controversial, and there are many methods available that require various (and sometimes different) assumptions (see Marsh et al., 2013). In our experience, it can be difficult to trust a model which involves estimating latent variable interactions because it is difficult to determine whether the resulting estimates of interactions are reasonable. Making things worse, different methods can produce different results and are vulnerable to assumption violations (e.g., Cham et al., 2012). We think most researchers would find the task of estimating latent variable interactions so daunting that the unknown effects that can result from ignoring measurement error would seem an acceptable price to pay in exchange for the ease of the analysis and interpretation when using an observed-variable modeling tool like PROCESS. But if you are up to the challenge, go for it. Perhaps in time, the methodology and technology for estimating latent variable interactions will become more intuitive and user-friendly.

Another reason a researcher might choose SEM over PROCESS is the greater flexibility an SEM program offers for model specification. The current release of PROCESS (v2.16) has 76 pre-programmed models that differ with respect to which and how many paths are moderated and by how many moderators, as well as the presence of various constraints such as effects fixed to zero. But if your model is different than these pre-programmed models, the only option available is to move to an SEM environment, which would allow you to estimate the model you desire at the expense of the additional effort required to write the code corresponding to that model. However, this benefit of SEM relative to PROCESS is diminishing. The next version of PROCESS (to be released in late 2017) includes options for modifying preprogrammed models or constructing a model from scratch.

SEM programs also offer measures of fit of the model to the data (e.g., RMSEA, CFI, etc.), whereas PROCESS offers no omnibus measure of model fit, so one cannot go away from an analysis using PROCESS with information about how well the complete model describes the data. However, several of the more popular models built into PROCESS are saturated, so fit by some measures would be perfect when these models are estimated using SEM. Furthermore, there are more important things in analytical life than good fit, especially given that any good fitting model typically has several minor variations with different interpretations that fit equally well (the *equivalent models* problem; MacCallum et al., 1993). When conducting a mediation or conditional process analysis, just as important (if not more) are the estimates of and inference about the effects involving the variables in the model and related statistics that are sensitive to the hypotheses of interest (such as conditional indirect effects and the index of moderated mediation).

Finally, some SEM programs offer more options than PROCESS for dealing with missing data, a fact of life in most empirical research. PROCESS requires complete data. If it doesn't get it, it will make it complete through listwise deletion. Missing data solutions that rely on some kind of literal imputation must be implemented before the use of PROCESS, and procedures that involve creating data where there are none all have flaws. Many SEM programs can implement more sophisticated missing data procedures that don't require actually creating data, such as full information maximum likelihood (FIML). Between these two extremes (listwise deletion and FIML) is *multiple imputation*, not available in PROCESS but an option in some SEM programs.

4. Conclusion

Our intention was to provide guidance to researchers interested in understanding the mechanisms of effects and their contingencies about how the PROCESS macro and SEM differ both in operation and results, and to offer considerations to ponder when making the choice between them. The greater flexibility of SEM, both in terms of model specification and handling missing data, as well as its ability to account for random measurement error when estimating relevant effects involving latent variables all make it an attractive choice. But that comes at the price of greater effort and programming skill required to calculate relevant statistics and methods of inference that PROCESS does automatically and painlessly. For models that are based entirely on observed variables, investigators can rest assured that it generally makes no difference which is used, as the results will be substantively identical. The choice, in that case, is inconsequential.

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