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Beyond a tandem analysis of SEM and PROCESS: Use of PLS-SEM for mediation analyses!

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Abstract

Mediation and conditional process analyses have become popular approaches for examining the mechanisms by which effects operate and the factors that influence them. To estimate mediation models, researchers often augment their structural equation modeling (SEM) analyses with additional regression analyses using the PROCESS macro. This duality is surprising considering that research has long acknowledged the limitations of regression analyses when estimating models with latent variables. In this article, we argue that much of the confusion regarding SEM's efficacy for mediation analyses results from a singular focus on factor-based methods, and there is no need for a tandem use of SEM and PROCESS. Specifically, we highlight that composite-based SEM methods overcome the limitations of both regression and factor-based SEM analyses when estimating even highly complex mediation models. We further conclude that composite-based SEM methods such as partial least squares (PLS-SEM) are the preferred and superior approach

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when estimating mediation and conditional process models, and that the PROCESS approach is not needed when mediation is examined with PLS-SEM.

Keywords
conditional process analysis, measurement error, mediation analysis, partial least squares, PROCESS, structural equation modeling

Introduction

In their quest to better understand and predict behavior, social scientists and particularly marketing researchers typically deal with constructs (i.e., latent variables) embedded in complex statistical models (e.g., Martínez-López Francisco et al., 2013). These constructs are used to measure broad ideas or thoughts about abstract concepts that researchers seek to investigate (Hair & Sarstedt, 2019). As constructs are—by their very nature—abstract entities, researchers typically use multiple items to measure them.

A statistical model reflects and visually represents relationships among constructs (Bollen, 2002). These relationships are derived from theory and imply that the independent constructs directly affect one or more dependent construct(s) without any systematic influences of other observable or unobservable variables (Pek & Hoyle, 2016). However, as this assumption rarely holds in practice, fully understanding the mechanisms through which constructs influence each other requires considering the role of other variables that directly or indirectly impact specific relationships. The two most prominently applied approaches through which this impact can occur are mediation and moderation (e.g., Aguinis et al., 2017; Borau et al., 2015).

Mediation is a research design in which a third variable, referred to as mediator variable, intervenes between two related constructs. More precisely, in a mediation analysis, researchers examine whether a change in the independent construct results in a change in the mediator variable, which in turn changes the dependent construct in the model (e.g., Demming et al., 2017). Figure 1(a) shows an example of a simple mediation model in which M_1 theoretically mediates the relationship between Y_1 and Y_2. In contrast, moderation is a research design in which a third variable directly impacts the strength or even the direction of a relationship between two other constructs (e.g., Dawson, 2014). Figure 1(b) illustrates an example of a simple moderation in which M_2 theoretically impacts the strength of the relationship of Y_1 on Y_2. Mediation and moderation can also be combined in that a moderator impacts one or more direct effects that constitute a mediating effect, also referred to as conditional process models. Figure 1(c) and (d) shows examples of two conditional process models, which are also known as moderated mediation (e.g., Edwards & Lambert, 2007). Of course, the models can be extended to accommodate multiple mediators and/or moderators.

To estimate cause–effect models with latent variables, researchers typically apply structural equation modeling (SEM). Two approaches to SEM have been proposed, which differ in the way they conceptualize measurement and estimate the model parameters (Jöreskog & Wold, 1982): factor-based and component-based SEM. Despite the conceptual differences, the approaches share the same basic advantages in that they (1) enable researchers to simultaneously analyze complex inter-relationships between observed and latent variables, and (2) account for measurement error inherent in the measurement of abstract concepts (Sarstedt et al., 2016). As such, both approaches to SEM are fully equipped for analyzing complex mediation and moderation models.

Nevertheless, when it comes to analyzing mediation or conditional process models with constructs, some researchers augment their SEM studies with separate regression analyses using Hayes's (2018) PROCESS macro for SPSS or SAS (e.g., Finoti et al., 2017; Giovanis, 2016;

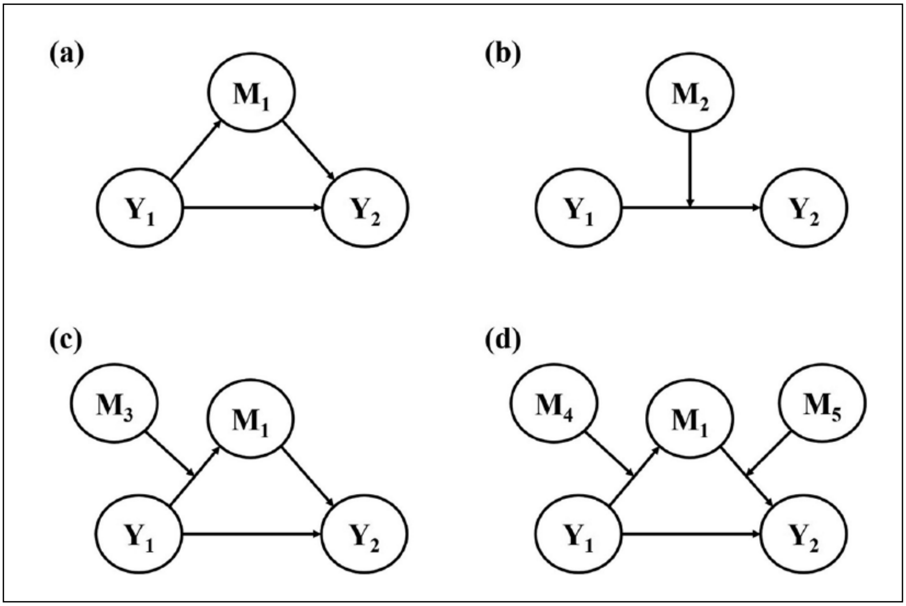

Figure 1. Mediation, moderation, and conditional process models.

Giovanis et al., 2015; Gong, 2018; Sakib et al., 2020). This duality in methods is surprising considering that numerous studies have contrasted SEM and regression-based mediation analyses on both conceptual and empirical grounds (e.g., Hayes et al., 2017; Iacobucci et al., 2007; Pek & Hoyle, 2016). Most of these studies clearly speak in favor of using SEM.

We believe that much of this confusion results from two developments: (1) many journal reviewers are not familiar with component-based SEM and require the results of the PROCESS approach to be reported, and (2) prior research on mediation in SEM has been strongly focused on factor-based methods. For example, in their contrasting of PROCESS and SEM, Hayes et al. (2017) highlight several limitations of SEM when estimating mediation and conditional process models. Their objections, for example, with regard to generating interaction terms or sample size requirements certainly have merit, but they only apply to factor-based SEM methods as executed by programs such as AMOS, LISREL, EQS, and Mplus. In contrast, composite-based SEM methods such as partial least squares (PLS-SEM; Hair, Hult, Ringle, & Sarstedt, 2017; Lohmöller, 1989) or generalized structured component analysis (GSCA; Hwang & Takane, 2004) offer researchers much more flexibility in terms of data requirements and specifying even highly complex models with multiple mediators and moderators (Nitzl et al., 2016). For example, composite-based SEM methods readily accommodate continuous moderators, allow estimating models with formatively measured constructs, and typically require smaller sample sizes compared with their factor-based counterpart (Hair et al., 2020). Overlooking these benefits of composite-based SEM methods paints an incomplete picture of the relative merits of SEM over PROCESS-based mediation and conditional process analyses.

Addressing these concerns, we discuss the role of estimating mediation effects in nomological networks and the impact of measurement error, which is inherent in construct measurement. While several of our descriptions apply to SEM in general, we place particular emphasis on aspects that distinguish composite-based SEM methods from their factor-based counterparts and which are relevant for analyzing complex mediation and conditional process models. In doing so, we focus on PLS being the most prominent composite-based SEM approach in the field (Hwang et al., 2020). Nevertheless, the following descriptions also apply to most other composite-based SEM methods.

PROCESS Versus PLS-SEM

PROCESS is a macro available for SPSS and SAS that simplifies the estimation of mediation and conditional process models. Rather than having to manually a specific model using syntax language, researchers using PROCESS can select from a broad range of models documented in Hayes et al. (2017). For each model, researchers must set specific arguments to identify (in)dependent variables, mediators, moderators, or covariates. PROCESS then runs separate ordinary least squares regressions in combination with bootstrapping to derive inferential statistics for the indirect effects.

PROCESS certainly has merit for estimating mediation and conditional processes in regression-based models with single-item observable variables. In addition, the intuitive use of PROCESS has made even complex mediation analyses accessible to researchers who are not experts in multivariate data analysis. However, PROCESS is subject to two limitations when it comes to handling complex cause–effect models with latent variables. Specifically, PROCESS-based analyses (1) are confined to estimating singular model structures in isolation, and (2) ignore the diluting effect of measurement error.

Estimating mediation effects in nomological networks

Decades ago, Jacoby (1978) noted that "we live in a complex, multivariate world [and that] studying the impact of one or two variables in isolation, would seem . . . relatively artificial and inconsequential" (p. 91). However, this is exactly what PROCESS does—assess the impact of a small number of variables in isolation. Consider the simple mediation model in Figure 1(a). To estimate this model, PROCESS runs two regressions: one regression of M_1 on Y_1 and another regression of Y_2 on Y_1 and M_1. In case of conditional process models, as shown in Figure 1(c) and Figure 1(d), the statistical model is augmented with interaction terms to map the moderating effects on one or more direct effects in the model. In either case, the parameter estimation in one regression has no effect on the parameter estimation in the other regression (Hayes et al., 2017). This approach is problematic for two reasons.

First, a piecemeal regression-based approach as executed in PROCESS treats the elements of the effect chain $Y_1 \rightarrow M_1 \rightarrow Y_2$ as separate processes (Spencer et al., 2005). This statistical handling is inconsistent, however, with understanding mediation as a single process (Pek & Hoyle, 2016). Even when combining the regression estimates into an indirect effect (as PROCESS does), the estimation still follows a piecewise approach rather than contemplating the model as a whole. As a consequence, researchers are discouraged "from thoughtfully puzzling over relations between the variables, leaving them less open to plausible, informative modifications of their initial model" (Pek & Hoyle, 2016, p. 159).

Second, each of the piecemeal regressions ignores other elements of the model, including potential antecedent constructs of Y_1, Y_2, or M_1. Iacobucci et al. (2007) show that such antecedent relationships can strongly impact mediation effects. Moreover, the resulting biases in parameter estimates become more pronounced when considering complex, sequential moderating effects involving multiple mediators, particularly mediators potentially embedded in a larger nomological network.

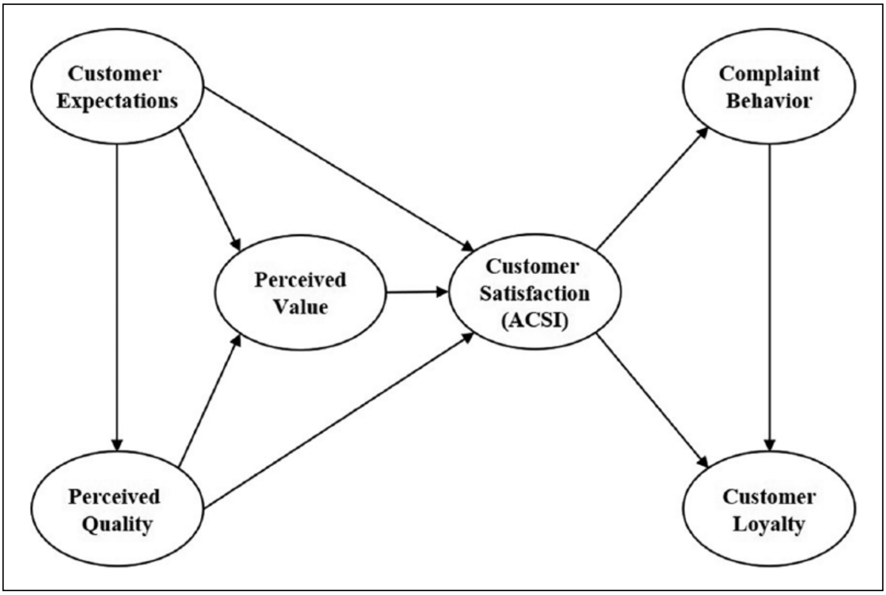

Figure 2. American Customer Satisfaction Index model (Fornell et al., 1996).

Different from PROCESS, PLS-SEM estimates the entire structural model relationships in a single analysis, thereby encouraging researchers to theorize about processes involving the constructs of interest in a plausibly larger nomological network (Nitzl et al., 2016; Pek & Hoyle, 2016). More precisely, PLS-SEM runs separate regressions of each dependent construct in the structural model on its associated independent constructs. Different from PROCESS, however, the PLS-SEM-based construct scores used as input for examining these relationships have been computed in an iterative process that considers the entire model structure. As a result, the iterative nature of the parameter estimations in PLS-SEM considers how the parameter estimations in the partial regressions impact each other. Because of its reliance on partial regressions, PLS-SEM reliably estimates parameters at low sample sizes, achieving high levels of statistical power (Hair, Hult, Ringle, Sarstedt, & Thiele, 2017; Hair, Sarstedt, & Ringle, 2019). Hence, sample size concerns encountered in factor-based SEM mediation analyses are not a concern in PLS-SEM.

To illustrate this point, consider the well-known American Customer Satisfaction Index model in Figure 2 (Fornell et al., 1996), which ranks among the most salient models in studying customer satisfaction and which has become a key performance indicator for companies and government agencies, as well as entire industries and sectors (Hair, Hult, Ringle, Sarstedt, & Thiele, 2017).

Researchers working with the ACSI could, for example, investigate whether Complaint Behavior mediates the relationship between Customer Satisfaction (ACSI) and Customer Loyalty. To estimate this mediating effect, both PROCESS and PLS-SEM run separate regressions of Complaint Behavior on Customer Satisfaction (ACSI) and Customer Loyalty on Customer Satisfaction (ACSI) and Complaint Behavior.[1] The approaches differ, however, in terms of the construct scores used as input for these regressions. Whereas PROCESS uses the sum or average of the indicators as input, thereby neglecting the antecedent constructs, PLS-SEM derives the construct scores in the context of the entire model (i.e., also taking into account Customer Expectations, Perceived Quality, and Perceived Value).

To resolve this limitation of PROCESS, researchers could specify and estimate the model using SEM and use the resulting construct scores as input for a subsequent PROCESS analysis. A major issue with this type of approach is that the construct scores produced by factor-based SEM are indeterminate, which means that an infinite number of different sets of construct scores will fit the model equally well (Steiger, 1979). This characteristic makes the construct scores produced by factor-based SEM grossly unsuitable for follow-up analyses such as those executed via PROCESS (see Schönemann & Haagen, 1987). In contrast, composite-based SEM methods linearly combine the indicators to compute weighted composite scores to represent the constructs. As a result, the construct scores produced by composite-based SEM methods can be considered determinate (Rigdon et al., 2019a). Using these scores as input in PROCESS, however, requires the researcher to specify the entire model—including all mediators and interaction terms in case of a conditional process analysis—exactly as it would occur in PROCESS. A subsequent PROCESS-based analysis offers very little additional insights, particularly since modern PLS-SEM software programs such as Smart-PLS (Ringle et al., 2015) or R packages such as SEMinR (Ray & Danks, 2019) include all relevant outputs such as bootstrapped confidence intervals for interpreting complex mediating effects.

Considering measurement error in mediation and conditional process models

To estimate mediation and conditional process models involving measures of abstract concepts, PROCESS first computes sum scores or averages of indicators measuring each construct. Using the ACSI model as an example (Figure 2), this would mean that researchers would first compute indicator sum scores or averages of all constructs involved. For Customer Satisfaction (ACSI), researchers would compute the sum score (or average) of the three items "Overall satisfaction," "Expectancy disconfirmation," and "Performance versus the customer's ideal product or service in the category" (Fornell et al., 1996).

This practice is problematic as it ignores the attenuating effect of measurement error. Numerous studies have shown that failure to correct for measurement error produces a combination of under- and over-estimation in the estimates of the entire nomological network (e.g., Cole & Preacher, 2014; Hair, Hult, Ringle, Sarstedt, & Thiele, 2017; Yuan et al., 2020). In contrast, SEM methods permit the elimination of measurement error in the analyses. In fact, the need to account for measurement error when estimating relationships among latent—as opposed to observed—variables was the primary motivation for the development of SEM (Jöreskog, 1973) and constitutes *the* primary advantage of this second-generation method over first-generation techniques like regression analysis, analysis of variance, *t*-tests, and many others (Cole & Preacher, 2014). Hayes et al. (2017) note that if one views the need to account for measurement error as crucial, it should be applied consistently to all first-generation techniques. We fully concur. In fact, the use of latent variable methods like SEM has proven uncontroversial in psychometrics, psychology, and many other fields, whenever researchers deal with abstract concepts. Marketing researchers should follow suit.[2]

Recent research has shown that correcting for measurement error is particularly critical when dealing with interaction terms—as required to specify a moderating effect in, for example, conditional process models (Li et al., 2019). The reason is that the attenuating effect of measurement error is exacerbated in the product of two error-prone measures (Cortina et al., 2020). For instance, when a predictor and moderator are uncorrelated, the reliability of the interaction term is the product of the predictor's and moderator's reliabilities (Aguinis et al., 2017; Busemeyer & Jones, 1983). Even in cases when the predictor and moderator demonstrate acceptable reliability (e.g., .80), the reliability of the interaction term can fall short of desired cutoffs (e.g., <.70). Edwards (2009) even refers to the notion that measurement error can be ignored as one of "seven deadly myths of testing moderation" (p. 143). Another issue is the interaction effects are typically small compared with the direct effects, thereby reducing the statistical power to detect interactions (Aguinis et al., 2005; Murphy & Russell, 2017). Any issues associated with measurement error are thereby even more so critical, as they could attenuate already small effects, so they are virtually undetectable if not properly addressed.

A common objection regarding the use of SEM for estimating conditional process models is that the estimation of interaction terms is far from trivial, and its specification is still subject to debate in the methodological literature (e.g., Cortina et al., 2001, 2020; Sardeshmukh & Vandenberg, 2017). Commenting on these issues, Hayes et al. (2017) note that "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" (p. 80). While this conclusion may apply when estimating interaction terms using factor-based SEM, this is not the case with composite-based SEM methods. Because these methods linearly combine the indicators to compute weighted composite scores, researchers can readily compute interaction terms analogous to regression analysis. Apart from the standard product indicator approach, which involves multiplying each indicator of the independent construct with each indicator of the moderator variable (Chin et al., 2003), researchers have proposed more complex approaches for generating the interaction term's measurement model (Becker et al., 2018). User-friendly software programs such as SmartPLS (Ringle et al., 2015) have options to include interaction terms based on these approaches by point-and-click operations, making even complicated conditional process analyses amendable to novice users. Therefore, there is no reason to shy away from using composite-based SEM when estimating interaction terms in conditional process models.

The use of composite-based SEM for conditional process models can address recent concerns regarding the application of latent approaches to test mediation effects but reverting to non-latent approaches (e.g., PROCESS) to test moderation effects within the same model (Cheung & Lau, 2017; Cortina et al., 2020; Sardeshmukh & Vandenberg, 2017). As Cortina et al. (2020) note,

> Using latent variable modeling for additive portions [i.e., the main effects] and dropping them for multiplicative portions [i.e., the interaction term] is akin to putting on the parking brake in Cleveland but leaving it off in Columbus: Either you think that the break does something worthwhile or you don't.

Composite-based SEM methods correct for measurement error, thereby improving the capability to accurately identify interaction effects (i.e., the analysis almost always exhibits meaningful statistical power). Given these considerations, no researcher should apply both latent and non-latent approaches to test different portions of their conditional process models. Instead, they should utilize composite-based SEM to estimate their entire model.

Leaving all of the above concerns regarding the impact of measurement error on parameter estimates aside, Rigdon et al. (2019a) have recently shown that using sum scores or averages of indicators further increases the uncertainty in the relationship between any construct measurement and the concept it seeks to represent (Rigdon et al., 2019b, 2020). That is, the measurement potentially becomes further detached from the actual entity the researcher wants to draw inferences about (Steiger, 1979). These findings further support the efficacy of composite-based SEM methods for estimating mediation and conditional process models.

Conclusion

To understand and explain complex causal processes, researchers in marketing and other business research disciplines often test mediation and moderation models, or combinations thereof. In fact, researchers are “increasingly [. . .] dedicating research efforts to understanding the mechanisms by which effects operate and the factors that influence the size or strength of those mechanisms” (Hayes & Rockwood, 2020, pp. 48–49).

Using the PROCESS macro has become the norm for executing mediation and conditional process analyses in many social sciences. But relying on regression analyses—as done in PROCESS—has been subject to considerable criticism when estimating models with latent variables since they (1) treat elements of the effect chains (structural model relationships) as separate processes, and (2) ignore the effect of measurement error. These problems are exacerbated in conditional process analyses (moderated mediation) as the interaction effect strengthens the attenuating effect of measurement error. In light of these issues, methodological researchers call for routinely using SEM to test mediation and conditional process models that involve latent variables (e.g., Iacobucci et al., 2007; Pek & Hoyle, 2016). Yet, in practice, researchers often augment their SEM with PROCESS analyses. We believe this confusion is due to the fact that (1) reviewers are not aware of the limitations of the PROCESS approach compared with composite-based SEM and that (2) prior research addressing the limitations of SEM in mediation analyses univocally focused on factor-based methods.

Composite-based methods such as PLS-SEM and GSCA are not subject, however, to the limitations of both regression and factor-based SEM analyses when estimating even highly complex mediation models. These methods not only account for measurement error and consider the entire model structure in the parameter estimation, but also offer more flexibility in terms of model specification compared with the factor-based SEM methods. Especially for conditional process models, researchers can easily integrate interaction terms while simultaneously accounting for measurement error. Using GSCA, researchers can extend such analyses to multi-item latent variable models with longitudinal and multi-level data (Hwang et al., 2007; Jung et al., 2012). These benefits come at drastically reduced demands in terms of sample sizes. For example, Hair, Hult, Ringle, Sarstedt, and Thiele (2017) simulation study using a model of similar structure as the ACSI shows that PLS-SEM achieves a statistical power of well above 90% for medium effect and low sample sizes ($n = 100$), even when only few indicators define the measurement models. Moreover, when effect sizes are small, the statistical power is higher than 80% in practically all model configurations—even when sample sizes are small. Hence, sample size considerations are seldom an issue when using PLS-SEM to estimate complex mediation models, including moderated mediation.

In light of these benefits, using component-based SEM for mediation and conditional process analyses should be the preferred option. There is no need for a tandem use of composite-based SEM and PROCESS—as indicated in some prior research studies (Memon et al., 2018).

A potential objection regarding the use of PLS-SEM compared with factor-based SEM could be that the method does not offer model modification indices to readily address potential problems of model misspecification as caused by, for example, omitted variables. However, recent research has introduced procedures for comparing PLS path models in terms of model fit and predictive power (Liengaard et al., 2020; Sharma et al., 2019, 2020). While these procedures do not provide a standalone assessment of a model, they allow contrasting different model configurations that vary, for example, the position of a moderator in a conditional process model.

Future research should further explore these procedures, particularly in the context of out-of-sample predictive power assessment (Shmueli et al., 2019). When testing a model’s predictive power, a mediator is considered the “piggy-in-the-middle” since its scores can be predicted both by antecedent constructs and by its own indicators. But the assessment of the model’s predictive power should rely on only one of these methods to avoid any confounding of predictive power induced by both the structural model and the mediator’s measurement model. To disentangle the predictive power of mediating models, Shmueli et al. (2016) suggest two approaches. Researchers should disregard the direct antecedents of either the mediator construct (direct antecedent approach) or its measurement model (earliest antecedent), but not apply both. Researching the efficacy of these two approaches in predictive comparisons of mediation models would be highly useful. Future studies should also systematically explore the boundary conditions for mediation analyses in composite-based SEM. For example, Hayes and Scharkow (2013) show that the bias-corrected bootstrap confidence intervals perform best in terms of statistical power, whereas the percentile method is more useful for minimizing type I errors. Researchers should assess whether these conclusions generalize to PLS-SEM and other composite-based methods.

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Notes

1. See Hair, Ringle, et al. (2019) for details regarding the partial least squares structural equation modeling (PLS-SEM) estimation of models with binary indicators.
2. Note that researchers typically refer to factor-based SEM in this context. However, composite-based methods such as PLS-SEM and generalized structured component analysis (GSCA) also correct for measurement error, even when estimating factor models (Henseler et al., 2014; Sarstedt et al., 2016).

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