PLS-SEM's most wanted guidance

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Abstract

Purpose – Partial least squares structural equation modeling (PLS-SEM) has attracted much attention from both methodological and applied researchers in various disciplines – also in hospitality management research. As PLS-SEM is relatively new compared to other multivariate analysis techniques, there are still numerous open questions and uncertainties in its application. Our research addresses this important issue by offering guidance regarding its use in contexts with which researchers struggle.

Design/methodology/approach – We examine the most prominent questions and answers posed in a well-known PLS-SEM discussion forum. We do so by using a text analysis technique to identify the most salient topics.

Findings – Our data analysis identifies three salient PLS-SEM topics (i.e., bootstrapping and significance testing, higher-order constructs, and moderation).

Research limitations/implications – The results allow us to address the PLS-SEM community's main methodological issues. We discuss each area separately, and provide explanations and guidelines.

Practical implications – Our guidelines on the most important PLS-SEM topics provide decision-making and application aids. In this way, we make a decisive contribution to clarifying ambiguities when applying the PLS-SEM method in hospitality management research and other disciplines.

Originality/value – There has as yet been no systematic analysis of this kind in the field of PLS-SEM; we therefore present the first research results. Our findings and recommendations provide guidance for PLS-SEM applications in hospitality research and practice.

Keywords – partial least squares, structural equation modeling, PLS-SEM, guidelines, text analytics

Paper type – General review

1. Introduction

Partial least squares structural equation modeling (PLS-SEM; Hair *et al.*, 2022, Hair *et al.*, 2018b) is a method for analyzing complex interrelationships between constructs and indicators. Originally developed by the Swedish econometrician Herman Wold (Wold, 1982), and subsequently substantially extended by Jan-Bern Lohmöller (Lohmöller, 1989), PLS-SEM has recently been massively disseminated through hospitality, tourism, and leisure research (Ali *et al.*, 2018, do Valle and Assaker, 2016, Kono and Sato, 2022, Usakli and Kucukergin, 2018), as well as through numerous other fields of scientific inquiry, such as computer sciences, engineering, environmental sciences, medicine, political sciences, psychology, and sociology. Recent studies in the hospitality field apply PLS-SEM to, for example, assess the factors driving contactless dining services as a protective behavior against COVID-19 (Yasami *et al.*, 2022), restaurant innovativeness's impact on Generation Z's destination image (Ding *et al.*, 2022), and the antecedents of customers' loyalty to mobile food delivery services (Su *et al.*, 2022). Several aspects have contributed to PLS-SEM's prominence in hospitality research and beyond (Sarstedt *et al.*, 2022b). An example is its causal-predictive nature that strikes a balance between explanation and prediction, perfectly fitting today's research environment, which is not only concerned with testing hypothesized models, but also with deriving managerial recommendations (e.g., Nunkoo *et al.*, 2020, Rosenbusch *et al.*, 2018) that are predictive by nature (Chin *et al.*, 2020, Hair and Sarstedt, 2021, Legate *et al.*, 2022, Sarstedt and Danks, 2021). Further, PLS-SEM allows researchers to estimate relatively complex models with many constructs and indicators (Chin, 1998, Richter *et al.*, 2016, Wold, 1982). Finally, PLS-SEM offers a large portfolio of advanced analysis techniques and complementary methods that facilitates the handling of complex analytical tasks and model constellations (see Table 8 in Sarstedt *et al.*, 2022a), which are also relevant for hospitality and tourism research (e.g., Sarstedt *et al.*, 2020).

The many available PLS-SEM resources that enable applied researchers to use the method, is another important factor contributing to its dissemination. Since the publication of Chin's (1998) primer on PLS-SEM and the release of his PLS-Graph software (Chin, 2003)—the first PLS-SEM software with a graphical user interface—numerous textbooks (e.g., Garson, 2016, Hair *et al.*, 2021c, Ramayah *et al.*, 2018, Wong, 2019) and tutorial articles (Hair *et al.*, 2019a, Legate *et al.*, 2022, Sarstedt *et al.*, 2020, Sarstedt *et al.*, 2021) have demonstrated how PLS-SEM should be applied. Review articles on the method's use have disclosed areas of misapplication (see Table 1.1 in Hair *et al.*, 2021c), thereby contributing to the increased quality of studies drawing on PLS-SEM. The release of several open source software packages, such as matrixpls, cSEM, and SEMinR, as well as commercial software, such as SmartPLS, XLSTAT, and WarpPLS, complements this development (for a PLS-SEM software comparison, see Memon *et al.*, 2021, Sarstedt and Cheah, 2019). Consequently, PLS-SEM has become part of the standard portfolio of multivariate analysis methods (Hair *et al.*, 2018a) available to researchers. In light of these developments, Hair *et al.* (2021b) conclude that PLS-SEM is no longer an alternative to covariance-based SEM, but has become a quasi-standard tool for analyzing complex relationships between observed and latent variables.

With the widespread use of PLS-SEM and the increasing scope of the method's capabilities, researchers new to the method find it increasingly difficult to apply this approach appropriately. While the numerous textbooks and tutorial articles on PLS-SEM facilitate learning to use it, many research situations require more advanced analyses and expert knowledge (Hwang *et al.*, 2020). It is therefore not surprising that review studies have disclosed misapplications of PLS-SEM, particularly in terms of more complex analysis tasks (Sarstedt *et al.*, 2022a, Sarstedt *et al.*, 2022c). Such misapplications are problematic, as they may perpetuate usage practices that have deservedly been criticized (e.g., Sarstedt *et al.*, 2022b, Sosik *et al.*, 2009).

There are abundant inquiries from users—both in discussion forums and on social media—about PLS-SEM, seeking answers regarding undertaking advanced analyses, solving problems with data, and interpreting the results. At the same time, some PLS-SEM users appear to be unaware of the recent guidelines and recommendations that have expanded the toolkit for PLS-SEM analysis and improved it significantly (Sarstedt *et al.*, 2022a, Sarstedt *et al.*, 2020). The road to researchers' and practitioners' widespread acceptance has therefore not always been easy and remains rocky.

To address these issues, prevalent topics that raise doubts and prompt user questions need to be clarified. To this end, we examine posts in a very popular PLS-SEM discussion forum by means of text analysis (Hair *et al.*, 2021a). Its results allow us to structure the vast number of comments in the forum and extract the most prevalent topics requiring clarification. Our analysis identifies three particularly relevant topics—bootstrapping and inference testing, higher-order constructs, and moderation—that we discuss in more detail later on. In doing so, we also consider topics that have not, or only vaguely, been discussed in prior research, such as the specification and evaluation of binary moderators and three-way interactions. Our research results are not only relevant for the hospitality management and tourism research fields, but also for scientists and practitioners in a range of disciplines wanting to use the PLS-SEM method.

2. Method

Our text analysis of researcher queries in a popular PLS-SEM user forum comprises the following three steps: (i) data extraction, (ii) term-list generation and curation, and (iii) analysis (Delen and Crossland, 2008, Ozaydin *et al.*, 2017). In step 1 (data extraction), we extracted comments posted in a prominent PLS-SEM discussion forum to identify the most relevant topics. We selected the SmartPLS discussion forum for this purpose (https://forum.smartpls.com/), as SmartPLS is the leading and most comprehensive PLS-SEM software (Memon *et al.*, 2021, Sarstedt and Cheah, 2019). For example, reviews of PLS-SEM use in operations management and marketing research (Bayonne *et al.*, 2020, Hair *et al.*, 2022) found that SmartPLS was applied in the vast majority of studies in these fields. The SmartPLS discussion forum has been active since SmartPLS 2's release (Ringle *et al.*, 2005); with thousands of publicly viewable posts, it is the most comprehensive platform of its kind on the PLS-SEM method. On May 31, 2022, we extracted the data from the FAQ (Methodology) subsection of the forum, using the R software package rvest (Wickham, 2021) for web-scraping. This program crawled through the 1,534 available topics and extracted all posts between the years 2010 and 2022. We focus on this part of the forum, because it is the subsection where users can ask questions related to various aspects of the PLS-SEM method and its application.

Step 2 (of the term-list generation and curation) involved the use of text mining tools to generate and curate the term list for analysis in the third step. We used the Text Explorer module of SAS software's JMP Pro 16.2 to iteratively transform the text into structured, analyzable data.

===== Insert Figure 1 about here =====

In the initial phase, we used the extracted posts from the SmartPLS forum to create the text corpus. Then, we applied tokenization to divide the text into tokens (e.g., words, symbols, phrases, or other meaningful elements), and to determine which of these were included in our analysis. For example, we decomposed the question "Which bootstrapping method should be used?" into seven tokens, namely "which," "bootstrapping," "method," "should," "be," and "used." Thereafter we used the list of tokens as input for further processing. For example, the software converted the whole corpus into lowercase letters, excluded common stop words, and applied stemming to avoid duplicating topics with slightly different terms (e.g., "mediation," "mediator," and "mediate")—the dots at the end of the terms in Figure 1 indicate that these terms have undergone the stemming process (e.g., leaving only "mediat·").

The software then created an initial terminology list from the tokens ordered by frequency. In addition, the software displays a phrase list showing the phrases' frequencies, allowing users to include phrases from this list in their terminology list. A phrase is a combination of frequently co-occurring unigram tokens into an *n*-gram (usually with *n* being a number between 2 and 4). For example, the software combines the unigrams "path·" and "coeffici·" into the bigram "path·coeffici"). When tokens are combined into a phrase and added to the terminology list, stemming rules are also applied to the tokens constituting the phrase, and the respective unigram tokens' frequencies are updated to avoid double counting. Following, Ozaydin *et al.* (2017), we manually reviewed each phrase with a frequency of at least ten and included those into the terminology list that made sense in the context of this study. We also manually excluded tokens by adding them to the stop word list, if they are unrelated to the context of our study (e.g., prepositions). These steps were carried out iteratively because of the steps' interdependence. Finally, we recoded certain tokens or phrases in order to group them and specify that they represent synonyms. For example, the phrases "second-order construct," "higher-order construct," and "hierarchical component models" have similar reference value, so that we recoded them into one phrase. In summary, we parsed 1,534 documents (or the number of cases) into 9,561 tokens from which we extracted 156 different terms. The analysis's result helped us create a list of the ten most mentioned terms which represent the most prevalent topics that researchers ask questions about in the forum (Figure 1).

The most frequently used term is about bootstrap-based significance, which occurs 214 times. The terms higher-order construct, moderation, mga, mediation, sample, formative, coefficient determination (R^2), discriminant validity, and prediction follow. The three most prevalent problems are each mentioned more than 150 times; these can therefore be considered particularly relevant for PLS SEM users. We therefore discuss the bootstrapping and inference testing, higher-order constructs, and moderation topics in detail in the next sections.

3. Assessing statistical significance by means of bootstrapping

Bootstrapping is a nonparametric procedure that assesses a parameter's variability by examining the estimates' distribution by means of resampling from the available sample data, instead of using parametric assumptions to assess the parameter's precision (Davison and Hinkley, 1997, Efron and Tibshirani, 1993). To do so, bootstrapping generates a large number of randomly drawn subsamples (with replacement) from the original dataset. The model estimates from these subsamples are then used for standard inference testing (i.e., calculating confidence intervals or p-values).

Hospitality researchers routinely use bootstrapping for the inference testing of model parameters (Ali *et al.*, 2018, do Valle and Assaker, 2016, Usakli and Kucukergin, 2018), but also for a range of other evaluation criteria, such as the HTMT criterion (Franke and Sarstedt, 2019). Despite hospitality researchers' frequent use of bootstrapping, there is still a plethora of practical concerns regarding its application. In this respect, researchers should pay attention to the following criteria: (i) the kind of bootstrap confidence intervals used, (ii) the sample size per bootstrap subsample, (iii) the number of bootstrap samples, and (iv) the significance level. Below we elaborate these as they arise in questions.

What kind of bootstrap confidence interval method should be used? Several approaches are available to construct confidence intervals from bootstrapping results. These include the studentized method, the bias-corrected and accelerated (BCa) approach, and the percentile method. Aguirre-Urreta and Rönkkö (2018) evaluated the efficacy of these approaches, finding that the percentile method performs best. This method uses the bootstrap estimates to identify the 2.5% and 97.5% percentiles (in case of a 5% significance level) of a parameter value's distribution. These percentiles then act as the confidence interval's lower and upper boundaries. In case of a highly asymmetric parameter distribution, researchers should apply the BCa approach, which corrects the percentile method for skewness (Hayes and Scharkow, 2013). Determining what makes a distribution "highly asymmetric" is, of course, subjective. However, when detecting clear violations of symmetry on inspecting the histogram (e.g., a multimodal distribution), they should be taken as obvious evidence in favor of the BCa approach. Consequently, PLS-SEM researchers should regard an assessment of the bootstrap distributions' histogram as routine.

What is the sample size per bootstrap subsample? The sample size per bootstrap subsample should be equal to the number of observations used in estimating the model. This also holds for group-specific analyses in, for example, multigroup analyses (Matthews, 2017). A smaller (larger) number of observations per subsample would systematically increase (decrease) the bootstrap standard error, thereby triggering type I and II errors. Most PLS-SEM software sets this number automatically, which should not be confused with the number of subsamples.

How many bootstrap subsamples should be used? In general, researchers should also use as many subsamples as possible. While basic research on bootstrapping (e.g., Davison and Hinkley, 1997, Efron and Tibshirani, 1993) has shown that even a few subsamples (e.g., 200 subsamples) can provide quite good approximations of the parameter distribution, more subsamples are always better. They increase the precision of the estimated parameter distribution and, therefore, the subsequent inference testing's precision. The only limitation here is the computing time, which, considering the high computing power available even with standard laptops, is no longer a general problem.

Figure 2 shows the difference between different bootstrap distributions in respect of 200, 500, 5,000, and 10,000 subsamples. The bootstrap distribution's approximation becomes more precise and, with it, important statistics' precisions, such as the standard deviation and the confidence interval boundaries. While initial model estimations can draw on a smaller number of bootstrap subsamples (e.g., 1,000), the final analysis should use at least 10,000 subsamples (e.g., Hair *et al.*, 2022, Chap. 4, Streukens and Leroi-Werelds, 2016). With such a high number of subsamples, random variations in the estimates are leveled out.[1]

===== Insert Figure 2 about here =====

Since bootstrapping aims to infer a parameter's distribution in terms of a specific population, the sample has to be representative of the intended population. Only if the given sample is representative of a population, will the bootstrap distribution match this population's distribution. Increasing the number of subsamples is no cure for representativeness problems and might even give a false impression of the precision if the sample and the population distribution do not align well.

Which significance level should be chosen and how should the effect sizes be interpreted? Researchers like to know which significance level they should use and whether a 10% probability of error is sufficient to interpret the results. It is difficult to make a general recommendation here. While many researchers recommend the commonly accepted 5% error level probability or the more conservative 1% error level probability, the trade-off between false positives (type I error) and power (type II error) always needs to be carefully considered (Cohen, 1994, Hair *et al.*, 2018a, Chap. 1). Determining the significance level implies the direct possibility of type I errors (i.e., the significance level is the type I error level). However, this decision also affects the type II error level. Researchers should therefore consider the cost of overlooking an existing relationship that the study finds nonsignificant (i.e., type II error level or statistical power). For example, what costs might managers incur if they do not know that a particular intervention has an effect on an outcome

[1] Note that some PLS-SEM software applications, such as SmartPLS 4, offer a fixed seed value for bootstrapping. In such a case, the results are always the same for different runs with the same number of subsamples (and if the other parameter settings are equal), because the algorithms always use the same random observation assignments. With random seed, the bootstrap results will, however, always be slightly different.

(e.g., improving hotel cleanliness to increase guest satisfaction)? How do these costs compare to those they incur if the intervention actually has no effect, even though research finds a significant relationship (type I error)? Some researchers set the acceptable error rate at 10% to achieve higher power. Nevertheless, generally, the more appropriate strategy is to use enough observations to achieve high power, while also using a more conservative threshold, such as a 1% error probability. To this end, researchers should perform a power analysis before conducting a study (Cohen, 1992, Crawley, 2015).

In general, the concept of significance is not particularly meaningful in itself, merely being an arbitrary distinction between two extreme outcomes. An effect with a p-value of 0.049 could be considered significant and recommended to policy makers and managers as important, while another effect with a p-value of 0.053 could be discarded as not significant and therefore not worthy of attention. Nevertheless, the uncertainty about both effects is almost similar. In addition, if the size of the sample used for model estimation is sufficiently large, virtually all coefficients, even the very small ones, become significant at the 5% or even 1% error probability level. A path coefficient of, say, 0.07 may be significant, but not particularly relevant, for explaining the target construct. Researchers should therefore not only consider whether effects are significant, but also whether they are substantial. In this regard, substantial could refer to explaining the variance in the outcome substantially, which could, for example, be investigated using the coefficients' f^2 effect sizes. Values from 0.02/0.15/0.35 can be considered weak/medium/strong effect sizes (Chin, 1998, Chin, 2010b); researchers could, as an alternative, check the coefficient's predictive validity (Chin, 2010a). Models' interaction terms, such as those in moderation (Becker *et al.*, 2018, Memon *et al.*, 2019) and quadratic effects (Basco *et al.*, 2021, Sarstedt *et al.*, 2020), lower the bounds of 0.005/0.01/0.025, which are considered weak/medium/strong effect sizes for assessing and interpreting results (Hair *et al.*, 2022, Chap. 7). Researchers should note that the probability of error levels for significance testing does not have to be (nor should be) adjusted for these interaction term or quadratic term effects.

4. Higher-order constructs

Higher-order constructs (also known as the hierarchical component model in the PLS-SEM context; Hair *et al.*, 2018b, Chap. 2, Lohmöller, 1989) allow researchers to simultaneously model a construct by means of a more abstract dimension (referred to as a higher-order component; HOC) and its more concrete sub-dimensions (referred to as lower-order components; LOCs). This type of modeling is well established in PLS-SEM applications in hospitality research (Ali *et al.*, 2018). For example, hospitality researchers have used higher-order constructs to measure consumer engagement with luxury brands (Le *et al.*, 2021), coopetition among hotels (Webb *et al.*, 2021), and luxury hotel brand coolness (Khoi and Le, 2022). While well established, many researchers have questioned (i) situations calling for the use of higher-order constructs, (ii) the types of model specification and estimation, and (iii) higher-order constructs' results evaluation and interpretation. We discuss these aspects below.

When to use higher-order constructs: Higher-order constructs give researchers an opportunity to extend standard construct conceptualizations, instead of relying on a single layer of abstraction. This enables the analysis of models' more abstract theoretical conceptualizations. According to Sarstedt *et al.* (2019), applying higher-order constructs has some benefits:

- They can help reduce a PLS path model's complexity.
- They allow researchers to overcome the bandwidth-fidelity dilemma (Cronbach and Gleser, 1965, p. 100), according to which there is a trade-off "between [the] variety of information (bandwidth) and [the] thoroughness of testing to obtain more certain information (fidelity)."
- They offer a way of addressing collinearity issues.

When considering higher-order constructs, it is not sufficient to simply combine constructs that appear to fit together in terms of their content (bottom-up approach). Such an approach is often used in applications to reduce the model's complexity but is rarely supported by a theoretical conceptualization of the (higher-order) construct. Instead, researchers should first conceptualize the higher-order construct and then establish its measurement by identifying LOCs (top-down approach) that adhere to the theoretical considerations. Another option is to utilize existing higher-level constructs from the literature. Researchers should, however, first carefully assess whether previous research established such higher-order constructs correctly and rigorously, or whether they were built in an ad-hoc, bottom-up approach without a solid theoretical grounding. If the desired higher order construct is neither available nor sufficiently established, researchers should instead include the LOCs as distinct constructs in the model. Since model complexity hardly affects PLS-SEM, researchers can execute such a procedure readily. Alternatively, researchers could initiate a project to develop the desired higher-order construct. However, this is usually a comprehensive, self-contained research project equivalent to that of scale development (e.g., DeVellis, 2016, Diamantopoulos and Winklhofer, 2001, Relling *et al.*, 2016). Such a project requires carefully justified theoretical considerations to establish a higher-order construct and arguments pertaining to the construct's conceptual definition, which goes far beyond simply reducing complexity. A reduction in complexity, or a more parsimonious model, does not provide sufficient arguments for establishing higher-order constructs if researchers do not provide theoretical reasons to do so.

Finally, when researchers are uncertain about measuring a theoretical concept by means of a higher-order construct, they could compare a model with higher-order constructs with an alternative model that only considers LOCs. If the model with the higher-order constructs achieves higher levels of model fit—as indicated, for example, by model selection criteria (Danks *et al.*, 2020, Sharma *et al.*, 2019, Sharma *et al.*, 2021) or the predictive power (Liengaard *et al.*, 2021, Sharma *et al.*, 2022)—its use would be empirically justified.

How to specify higher-order models: Based on theoretically established higher-order constructs, researchers need to determine (i) the LOCs' measurement model specification, and (ii) the relationship between the HOC and its LOCs (Jarvis *et al.*, 2003, Wetzels *et al.*, 2009), both of which can be reflective or formative by nature. In keeping with the latter, four core types of higher-order constructs evolve (e.g., Cheah *et al.*, 2019, Ringle *et al.*, 2012, Sarstedt *et al.*, 2022a), as displayed in Figure 3: reflective-reflective (Type I), reflective-formative (Type II), formative-reflective (Type III), and formative-formative (Type IV). Technically, PLS-SEM is able to accommodate these different types of higher-order constructs (for detailled guidelines see, for example, Hair *et al.*, 2018b, Chap. 2, Sarstedt *et al.*, 2019).

===== Insert Figure 3 about here =====

Sarstedt *et al.*'s (2022a) review study on PLS-SEM's use in marketing reveals that Type I and Type II higher-order models are used the most, with Type IV being rarely used. In addition, the use of reflective-reflective higher-order constructs (Type I) has been widely debated. Critics argue that such models do not exist (or are meaningless), implying that the indicators should be directly linked to the primary source of reflection—that is, the HOC (Mikulić, 2022)—because reflective constructs imply unidimensionality and redundant measures, which do not correspond to the concept of having distinct construct subdimensions. Psychometric theory, however, has long established that indicators can serve as measurements of more than one construct (Bollen, 1989). Consequently, the assumption that highly correlated indicators in the LOCs' measurement model imply high indicator correlations with all other LOCs stands on quicksand—as is thoroughly discussed in the literature (Temme and Diamantopoulos, 2016). In addition, reflective-reflective higher-order constructs can also be used in settings where the LOCs represent different measurements of a concept at different points in time (i.e., different batteries of a test sequence), which the HOCs also explain.

How to estimate higher-order models: A series of questions relates to estimating higher-order models. To date, four main approaches have been proposed to estimate higher-order constructs: (i) the repeated indicator approach, (ii) the extended repeated indicator approach, (iii) the embedded two-stage approach, and (iv) the disjoint two-stage approach (e.g., Cheah *et al.*, 2019, Sarstedt *et al.*, 2019). Since all approaches generally yield similar results (Cheah *et al.*, 2019), there is often no compelling reason to prefer one over the other. However, we recommend the two-stage approaches, because they find ways around problems that occur in specific model constellations, and because of their simple implementation in modern PLS-SEM software. We therefore focus our discussions on the two-stage approaches, while mentioning the (extended) repeated indicators' approach where applicable.

The embedded two-stage approach (Ringle *et al.*, 2012) and the disjoint two-stage approach (Agarwal and Karahanna, 2000, Becker *et al.*, 2012) differ regarding the first stage's modeling. While the embedded approach models the entire higher-order construct in its first stage by repeating the LOCs' indicators to identify the HOC, the disjoint approach initially only draws on the LOCs and connects them to all to the higher-order construct's antecedents and consequences. Figure 4 (Panel A and Panel B) shows the first stage of the embedded and disjoint two-stage approaches. In both cases, it is important to evaluate the LOCs' measurement in this stage by using the formative and reflective measurement model evaluation's common set of criteria (Hair *et al.*, 2019a, Sarstedt *et al.*, 2021). Researchers should only continue with the second stage if the LOCs meet the measurement model evaluation criteria.

===== Insert Figure 4 about here =====

A particular point of concern relates to the use of the correct estimation mode (i.e., Mode A or Mode B) to estimate the relationships between the HOC and its LOCs when applying the repeated indicators approach (Sarstedt *et al.*, 2019)—either in isolation, in its extended version, or in the first stage of the embedded two-stage approach. Researchers often choose the estimation mode in accordance with the relationships between the HOC and its assigned indicators. However, this default setting is wrong in the case of Type II and III models where the LOCs' measurement specifications and their relationships with the HOC are not the same. The HOC's estimation mode should rather correspond to its relationships with the LOCs (e.g., Becker *et al.*, 2012). Researchers should therefore use Mode A for a reflectively specified higher-order construct (i.e., the reflective-reflective Type I and the formative-reflective Type III) and Mode B for formatively specified higher-order constructs (i.e., the reflective-formative Type II and the formative-formative Type IV). Table 1 summarizes these recommendations. Note that the disjoint two-stage approach does not assign the LOCs' indicators to an HOC (Figure 4, Panel B); consequently, the model estimation can use standard algorithm settings for both stages (i.e., Mode A for reflectively specified measurement models and Mode B for formatively specified measurement models).

===== Insert Table 1 about here =====

Stage two of the embedded and disjoint two-stage approaches are similar, since they use the latent variable scores—obtained from stage one—as the HOC indicators (Figure 4, Panel C and Panel D). However, researchers face another uncertainty: the second stage's specification of the other (non-hierarchical) constructs. When applying the *embedded* two-stage approach, all non-hierarchical constructs need to be measured using single items that use the latent variable scores from the first stage as input (Figure 4, Panel C). In this case, all the non-hierarchical construct are only assessed in the first stage, because they use single items in the second stage, while the HOC's measurement model, which uses multiple items of the LOC scores from the first stage, needs to be assessed in this second stage. When using the *disjoint* two-stage approach, however, only the LOC scores from the first stage are used as input for the second stage HOC indicators; all the other (non-hierarchical) constructs are measured with their original indicators (Figure 4, Panel D). In this case, researchers need to evaluate all the construct measures in the second stage and not only those of the HOC. While the results of these two approaches do not differ significantly, we recommend using the disjoint two-stage approach, as this allows researchers to use $PLS_{predict}$ or (Shmueli *et al.*, 2016, Shmueli *et al.*, 2019) or CVPAT procedures (Liengaard *et al.*, 2021, Sharma *et al.*, 2022) to estimate the model's predictive power on an indicator level.

Finally, researchers seem to be unsure about which of the following weighting scheme to choose to estimate the structural model: (i) centroid, (ii) factor, or (iii) path (Lohmöller, 1989). Based on prior simulation results (e.g., Becker *et al.*, 2012), we recommend the path weighting scheme as the default setting when estimating higher-order constructs in PLS-SEM (Sarstedt *et al.*, 2019).

How to assess higher-order models: A major concern with the use of higher-order constructs relates to validating their measurements. In order to do so, researchers need to consider two steps. First, the LOCs' measurement models need to be validated by using the standard model evaluation criteria applied to standard constructs (Hair *et al.*, 2018b, Chap. 2). Only if the LOCs' measures are reliable and valid should researchers move on to the second step (i.e., evaluating the higher-order construct's measurement model as a whole). This measurement model is defined by its relationships with the LOCs. Evaluation in the second stage of both two-stage approaches is therefore straightforward and intuitive, because the LOCs are used as indicators of the higher-order construct. However, if the repeated indicators approach is, for example, used to identify the higher-order construct in stage one of the two-stage approaches, researchers need to pay particular attention. The relationships between the HOC and its (repeated) indicators—reported in extant

PLS-SEM software—do not indicate the higher-order construct's validity. The actual measurement model of the higher-order construct is represented by the relations between the HOC and its LOCs. These appear as structural model relations in a PLS path model, but are interpreted as loadings (in the case of Type I and II models) or as weights (in the case of Type II and IV models), respectively. Consequently, researchers need to manually calculate the relevant statistics for assessing, for example, the internal consistency reliability and the convergent validity of reflectively specified higher-order constructs when using the repeated indicator approach—see Sarstedt *et al.* (2019) and Hair *et al.* (2021b) for detailed descriptions.

Our analysis has shown that researchers often encounter two main issues when evaluating formatively specified higher-order constructs: (i) the absence of an alternative measure of the higher-order construct to be used as a criterion variable in a redundancy analysis (Cheah *et al.*, 2018), and (ii) dealing with nonsignificant LOC weights in Type II and IV models. In terms of global items, researchers need to consider their inclusion in the data collection stage. Failure to do so means that researchers cannot undertake the redundancy analysis as a means of assessing the convergent validity (Cheah *et al.*, 2018, Hair *et al.*, 2022, Chap. 5). With regard to dealing with nonsignificant LOC weights, researchers should not automatically interpret this finding as indicative of poor measurement model quality and discard the LOCs from the HOC, since such a step could have adverse consequences for the content validity. Instead of mechanically deleting the LOC with nonsignificant weights, researchers should assess the LOC's loading, which is equivalent to its bivariate correlation with the HOC. This correlation represents the LOC's absolute contribution and should be larger than 0.50 if the weight is nonsignificant (Hair *et al.*, 2022, Chap. 5).

Finally, when estimating any model with a higher-order construct, researchers should apply the standard structural model evaluation criteria (e.g., Chin, 1998, Hair *et al.*, 2019a, Tenenhaus *et* *al.*, 2005). However, when doing so, they should not consider the LOCs as elements of the structural model if they use the repeated-indicator approaches.

5. Moderation

PLS-SEM's application is often based on the assumption that the analyzed data stem from a (single) homogeneous population. This assumption is nevertheless mostly unrealistic, as respondents are often heterogeneous in terms of, for example, their demographic (e.g., age, gender, income), geographic (e.g., country of origin), or psychographic (e.g., attitudes, values, lifestyle) characteristics (Wedel and Kamakura, 2000). Consequently, many researchers have used PLS-SEM to investigate moderation models in which a relationship's strength between two constructs is a function of a third construct called the moderator (Hair *et al.*, 2022, Chap. 7, Memon *et al.*, 2019). For example, hospitality researchers have evaluated the moderating impact of consumer materialism on luxury hotel brand perceptions' effect on brand satisfaction (Le *et al.*, 2021), or the impact of employees' values on individual eco-friendly behavior's effect on a hotel's environmental performance (Raza and Khan, 2022). Assessing such a moderating effect helps researchers determine "when" or "for whom" a construct explains an outcome construct (Frazier *et al.*, 2004), thereby offering important insights into real-world functioning mechanisms. However, researchers often question (i) whether the model should be analyzed with or without the moderator being included, (ii) how the interaction term should be generated, (iii) how binary moderators should be handled, and (iv) how a three-way interaction analysis should be conducted. We address these questions below.

Should the model be analyzed with or without the moderator being included? Researchers often ask whether they need to include the moderator directly in the model, or whether they should first estimate a model without a moderator. To answer this question, the following three scenarios need to be decided: The aim of the study is

1) to test the moderating effect, while the direct effect being moderated is not subject to hypothesis testing.
2) to test the moderating effect, as well as the direct effect being moderated.
3) not to test a moderating effect, but rather to investigate ex post facto whether the direct effect is stable, or depends on certain contextual factors (which are theoretically plausible, but not an explicit part of a model or theory). This analysis is often regarded as a robustness check (e.g., Sarstedt *et al.*, 2020).

In the first scenario, researchers should add the moderator directly and only analyze this model. If moderation is assumed (and the moderator is significant), it makes little sense to analyze a model without the moderator (i.e., an unconditional main effect model).

This, however, differs in the second scenario (Becker *et al.*, 2018, Hair *et al.*, 2022, Chap. 7). When hypothesizing a direct main-effect relationship, the corresponding effect should be estimated without the moderator being included. This is due to the effect changes' interpretation when a moderator is included in the model. Instead of representing an average effect, this relationship now quantifies the effect of a construct on the criterion construct when the moderator value is zero, which is at the moderator's mean—assuming that researchers standardize or mean-center the moderator, as is commonly done in PLS-SEM studies. Any testing of a direct effect is therefore now conditional on the moderator's mean value, which is not on par with a formulated main-effect hypothesis (which is usually an unconditional hypothesis). Researchers should therefore first establish a base model without including the moderator to test the direct effect's significance. Thereafter, they should include the moderator to assess its impact. At the same time, researchers should be aware that a significant moderator provides evidence that the direct effect—as estimated in a model without the moderator—is misleading, because the estimate is subject to heterogeneity.

Finally, when conducting a post moderation analysis, it is advisable to first analyze the model without moderation (i.e., the hypothesized research model) and to undertake additional moderation analyses in the next step. In such analyses, researchers should keep in mind that the effects' interpretation changes as soon as a moderating effect is included in the model (Hair *et al.*, 2022, Chap. 7).

How should the interaction term be generated? The PLS-SEM literature discusses three approaches to generate the interaction term that maps the independent and moderator constructs' joint impact on the criterion construct. In the past, the structural equation modelling literature often relied on the product indicator approach that cross-multiplies all of the moderator construct's indicators with those of the independent variable to define the interaction term's measurement model. However, in PLS-SEM, research has shown that this approach lags behind in terms of statistical power and parameter accuracy (e.g., Becker *et al.*, 2018, Henseler and Chin, 2010). Researchers should instead rely on the two-stage approach, which uses the construct scores from a model estimation without the interaction term in stage one as input to compute the interaction term in stage two. However, this approach cannot be easily implemented manually, because, in the second stage, the interaction term (the latent variables scores' product) should not be standardized, which would happen if researchers were to simply enter its scores in a normal PLS path model. Researchers should therefore rely on PLS-SEM software that computes this for them (e.g., SmartPLS, cSEM, SEMinR, and WarpPLS).

How should binary moderators be handled? A binary variable is a categorical variable with only two possible values (e.g., yes/no, response/no response, true/false, etc.) and is usually represented by a dummy-coded (0/1) variable (e.g., Sarstedt and Mooi, 2019). When researchers use such a binary moderator variable in a path model, the routine standardization of all input variables in PLS-SEM creates certain complications regarding interpreting the moderator's effects.

Researchers should remember that if the moderating effects are included in the model, the path coefficients become simple or conditional effects, which are then interpreted relative to the reference point zero. With unstandardized variables, this reference point is the actual zero value of the variable (regardless of whether this zero value is defined for the variable or not, for example, as on a 1 to 5 Likert scale, where zero is not defined). Consequently, mean-centering or standardizations often allow moderation effects to be better interpreted, because the zero reference point will be the variable's mean. Nonetheless, the interpretation of a standardized binary variable is complicated by mean-centering or standardization, because the reference point (the mean value) lies somewhere between the two categories, thereby not quantifying any meaningful value. Although this reference point is not interpretable, the model is still correctly estimated, and manual computations can retrieve correct interpretable effects. It is also important for a moderation analysis that the binary variable is dummy coded as 0/1 and not, for example, as 1/2, because this causes similar complications regarding interpreting the effects, as the reference point is always zero, but zero is not a possible value for a 1/2 coded variable.

Consider a simple model in which a researcher hypothesizes that the room type (standard = 0 vs. premium = 1) moderates the relationship between customer satisfaction and loyalty. Assume that the PLS-SEM estimation of such a model would produce the results shown in Table 2. The estimated customer satisfaction on customer loyalty effect of 0.5017 is the conditional effect when the room type is zero, which is at the mean value of the original variable after mean centering or standardizing the data. However, the mean room type is an arbitrary value without a meaning. Likewise, the interaction effect does not represent the change in satisfaction's strength when we switch from one room type to another, but again depends on the standard deviation changes that do not make any sense in respect of binary variables (only regarding metric variables). Researchers need take the binary variable's standardization into account to obtain estimates that are interpretable and do a few manual corrections, or ensure that the room type is not standardized during the PLS-SEM algorithm.

===== Insert Table 2 about here =====

Researchers need to follow the following steps to apply the manual corrections. First, the researcher needs to determine the standard deviation change that a category change (i.e., a switch from standard to premium) implies. Assume that, in our example, a room type's standard deviation is 0.4817 and the mean 0.6366 (implying that 63.66% of the customers have booked a premium room). The values of a standardized room type variable are therefore:

Standard: $\frac{(0-mean)}{std.dev.} = \frac{(0-0.6366)}{0.4817} = -1.3236$, and

Premium: $\frac{(1-mean)}{std.dev.} = \frac{(1-0.6366)}{0.4817} = 0.7555$

This implies that a category change is equal to |-1.3236| + 0.7555 = 2.0791 standard deviations. Second, researchers need to correct the standardized coefficients (Table 2) by multiplying them with this number, because we are not interested in a standard deviation change (which, in a binary variable, has no meaning), but in the category change. A room type's effect on customer loyalty is therefore 0.004 · 2.0791 = 0.0084. Likewise, the moderating effect can be calculated as -0.0216 · 2.0791 = -0.0449 (Table 2). Third, we need to determine customer satisfaction's effect on the customer loyalty in respect of both room types. The standardized estimate is 0.5017, which implies that room type has a value of zero (which is the original variables' mean, after mean centering or standardization), which represents neither standard nor premium room customers.

Using the above information, we can calculate the effect for each category (the conditional direct effects) as follows:

- The effect of standard room customers is 0.5017 + (-1.3236 · -0.0216) = 0.5303 and

- its effect on premium room customers' loyalty is 0.5017 + (0.7555 · -0.0216) = 0.4854.

The difference between the two is therefore 0.5303 – 0.4854 = 0.0449 (i.e., the corrected moderation effect that we calculated before). Researchers using binary moderators should consider these corrections carefully, since standard PLS-SEM software usually only reports the raw results—as displayed in Table 2. The PLS-SEM software SmartPLS 4 (Ringle *et al.*, 2022) supports researchers' analyses by allowing not standardizing binary variables, and therefore does not require manual corrections.

How should a three-way interaction analysis be conducted? Occasionally, researchers need to simultaneously consider multiple moderators for a given relationship in their model. While these moderators may individually impact a relationship, they can also be interconnected and influence each other's impact. Consider, for example, a simple PLS path model in which the respondent's income (M_1) moderates the relationship between customer satisfaction (Y_1) and customer loyalty (Y_2). We could extend this two-way interaction (two-way because Y_1 interacts with M_1) by adding a second moderator age (M_2) to the model, which is hypothesized to influence the strength of the initial moderating effect. In other words, the moderating effect of M_1 depends on another moderator M_2, such that M_1 moderates the relationship between the independent variable (Y_1) and the dependent variable (Y_2) as a function of M_2. Figure 5 illustrates this model constellation, which is also referred to as a three-way interaction (Aiken *et al.*, 1991).

===== Insert Figure 5 about here =====

Panel A in Figure 6 illustrates how this three-way interaction is implemented in a PLS path model. M_2 impacts all the relationships in of a two-way interaction model with M_1. Panel B in the same figure shows how the three-way interaction is estimated in PLS-SEM (see also Henseler, 2021, Chap. 11):

$$Y_2 = \beta_0 + \beta_1 \cdot Y_1 + \beta_2 \cdot M_1 + \beta_3 \cdot M_2 + \beta_4 \cdot Y_1 \cdot M_1 + \beta_5 \cdot Y_1 \cdot M_2 + \beta_6 \cdot M_1 \cdot M_2 + \beta_7 \cdot Y_1 \cdot M_1 \cdot M_2. ,$$

whereby β_0 represents the constant term (or intercept), that is zero when using standardized data, as is common in PLS-SEM, and is therefore not included in Figure 6.

In in this three-way interaction, the model contains three simple effects (β_1 to β_3), three two-way interaction effects (β_4 to β_6), and one three-way interaction (β_7). To correctly estimate the model, it is again important that all the lower-level effects are included in the model if higher-level interactions are present. In this case, the latter implies that as soon as we want to estimate the three-way interaction represented by β_7 ($Y_1 \cdot M_1 \cdot M_2$), we need to include all three possible two-way interaction terms (i.e., $Y_1 \cdot M_1$, $Y_1 \cdot M_2$, and $M_1 \cdot M_2$), even if we do not want to focus on or directly interpret some of these interactions.

===== Insert Figure 6 about here =====

Similar to a two-way interaction (Memon *et al.*, 2019), researchers should draw on the two-stage approach to estimate models with three-way interactions. The first stage provides the standardized construct scores. These scores are then multiplied to generate the interaction terms that capture the joint effects of Y_1, M_1, and Y_2. The standardized latent variable scores are usually used for this multiplication. However, similar to the two-way interaction, the resulting product should not be standardized, and the researcher should estimate and interpret the unstandardized coefficient.

Until recently, most PLS-SEM software did not allow users to readily implement three-way (or higher) interactions. Consequently, researchers had to manually calculate the interaction terms, which is a frequent source of error because, all the input variables' routine standardization in PLS-SEM, does not allow the interaction term (product term) to be used to build the second stage in a normal PLS model. Researchers therefore need to implement the correct second-stage regressions themselves. However, PLS-SEM software, such as SmartPLS 4 or cSEM, allows researchers to model interactions with two or more moderators.

6. Discussion and Conclusion

PLS-SEM has become an integral part of the multivariate analysis methods' portfolio in the social sciences (e.g., Hair *et al.*, 2018a, Chap. 13), which includes hospitality management and tourism research (Ali *et al.*, 2018, do Valle and Assaker, 2016, Usakli and Kucukergin, 2018). Continuous methodological development increases PLS-SEM's value as an instrument in the toolbox for studies on hospitality management and tourism research, but also on business and management research in general (for an overview of PLS-SEM developments see Table 9 in Sarstedt *et al.*, 2022a). At the same time, software applications, such as SmartPLS, XLSTAT, and WarpPLS (for a PLS-SEM software review, for example, see Memon *et al.*, 2021, Sarstedt and Cheah, 2019), require relatively little effort to execute PLS-SEM analyses, making the method available to researchers with little background in statistics. This development has been criticized (for example, see Antonakis *et al.*, 2010), although this criticism parallels discussions during Apple computers' proliferation in the 1990s and the view sometimes articulated at the time that people were using computers despite their lack of technical knowledge. Similarly, information systems fully understand that, to meet consumer needs, new technologies should be easy to use. We regard statistical methods' development, particularly that of PLS-SEM, in a similar way. Methodological researchers should therefore make complicated developments accessible to a broader audience and offer concrete guidance for their applications.

Our research makes an important contribution to this development. We address researchers' most pressing questions about the use of PLS-SEM, focusing on bootstrapping-based significant testing, higher-order constructs, and moderation—topics featuring prominently in hospitality management and tourism research. Our explications and answers provide guidance for applying the method effectively, while also clearing up uncertainties prevalent in users' questions in a popular PLS user forum. Table 3 summarizes the key questions, as well as our proposed answers and recommendations.

===== Insert Table 3 about here =====

Future research should address new and expanded issues of the topics discussed in this paper. Such assessments could also draw on the qualitative inquiries (Sarstedt and Mooi, 2019, Chap. 4) of heavy users and methodologists working with PLS-SEM in an effort to identify further pressing issues. At the same time, researchers harbor uncertainties about many other important areas (Figure 1, Panel B), which follow-up research should also address. Further topics that feature less prominently in current discussions, but are expected to gain momentum include, for example, the necessary condition analysis (Dul, 2020, Richter *et al.*, 2020), endogeneity assessment (Becker *et al.*, 2022, Hult *et al.*, 2018), model fit testing (Hair *et al.*, 2019b), and dealing with heterogeneity (Becker *et al.*, 2013, Hair *et al.*, 2018b, Chaps. 4 & 5). While only focused our discussions on three topics, we are confident that our descriptions provide researchers and practitioners with guidelines offering clear direction, also in terms of error prevention. Furthermore, we challenge PLS-SEM software's developers to improve the program so that application errors become impossible. These developments would make an important contribution to PLS-SEM's satisfactory use in research and practice, which is crucial for the method's usefulness and its continued high diffusion in business research, as well as in hospitality management and tourism research.

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Figures

Term and/or Phrases	Count	Visualization Result
1) bootstrap· signific·	214	
2) higher order construct	172	
3) moder·	151	
4) mga·	125	
5) mediat·	118	
6) sampl·	115	
7) format·	109	
8) coefficient determination - R^2·	59	
9) discriminant valid·	50	
10) predict·	43	

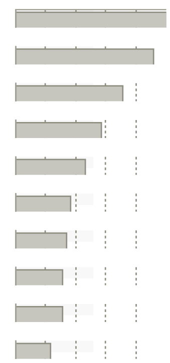
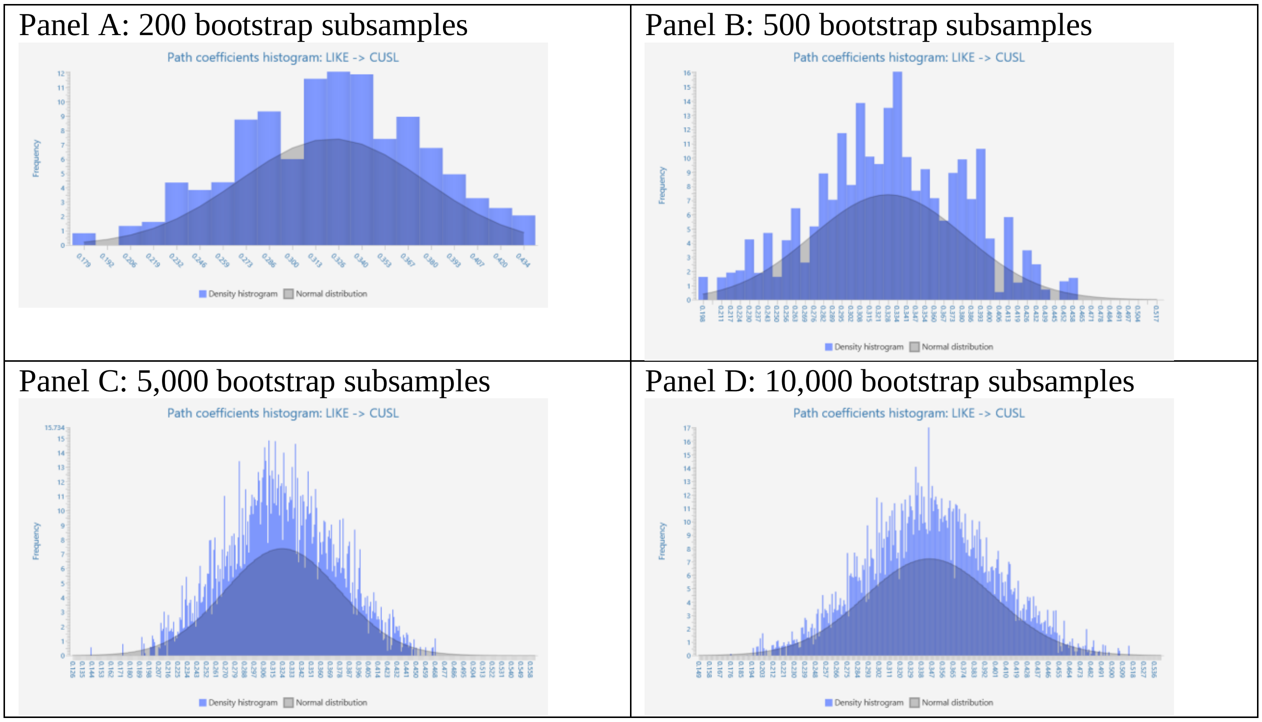
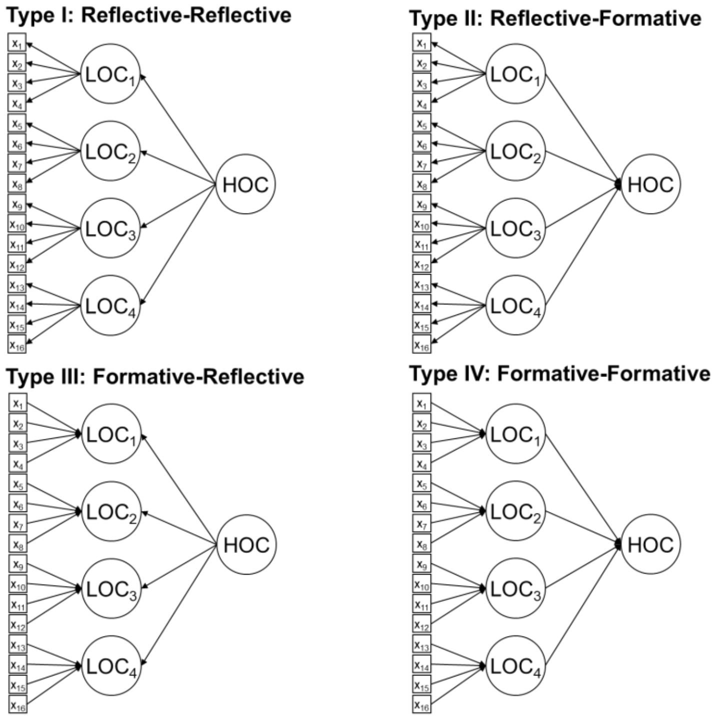


Figure 1. Top terms and phrases



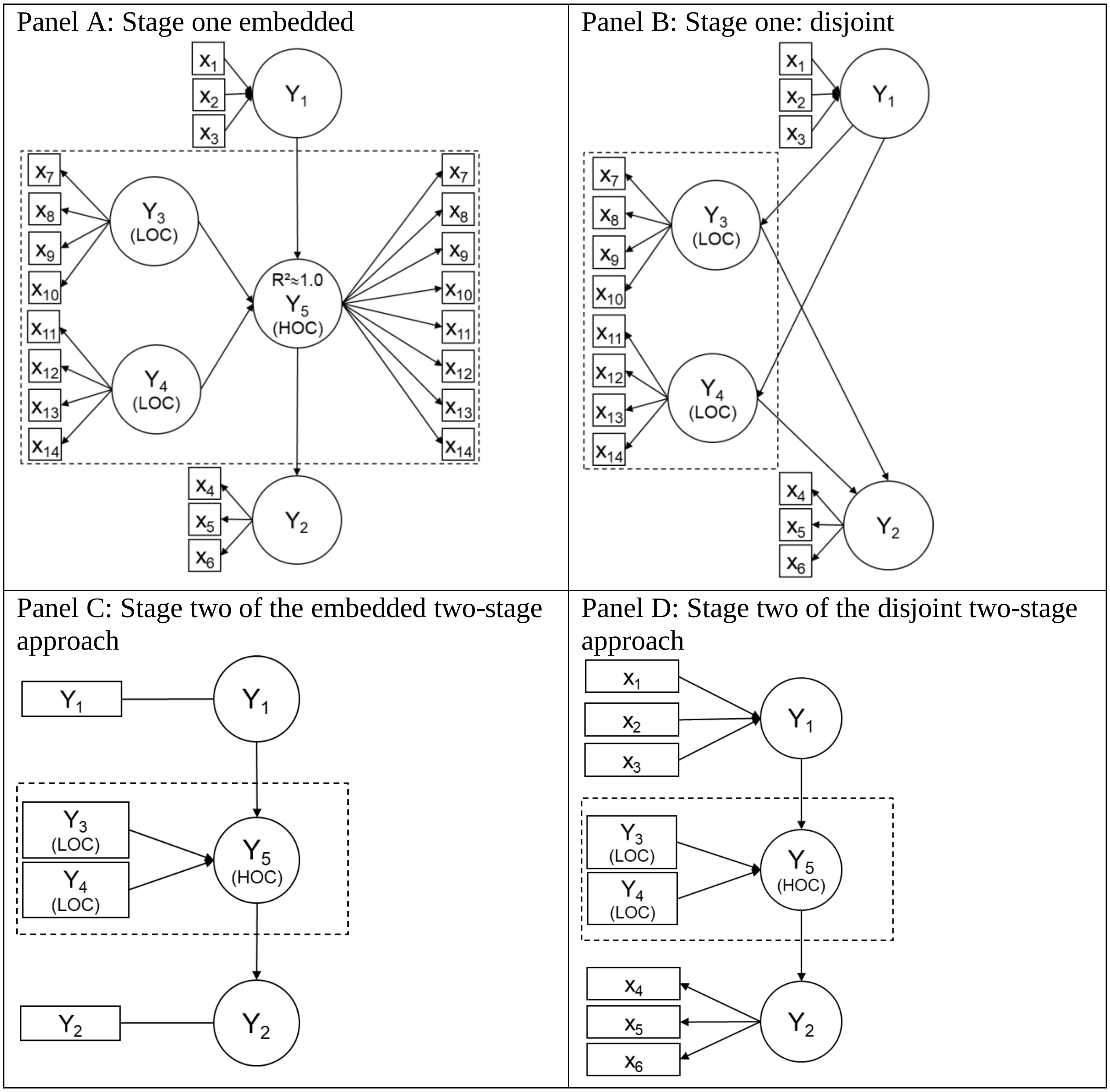
Note: The figure displays bootstrap distributions of the relationship between the constructs' likeability (LIKE) and the corporate reputation model example's customer loyalty (CUSL) (Hair *et al.*, 2022). The figures were extracted from SmartPLS 4 (Ringle *et al.*, 2022) by using the percentile approach and the default bootstrapping settings.

Figure 2. Comparison of bootstrap distributions with different numbers of subsamples



Note: LOC = lower-order component; HOC = higher-order component; the indicators of the LOCs (i.e., x_1 to x_{16}) are also assigned to the HOC to estimate the higher-order model. The figure was adopted from Sarstedt et al. (2019).

Figure 3. Higher-order construct types



Note: HOC = higher-order component; LOC = lower-order component; LV scores = latent variable scores. The figure was adopted in a modified version from Sarstedt et al. (2019).

Figure 4. The two-stage approach for higher-order models

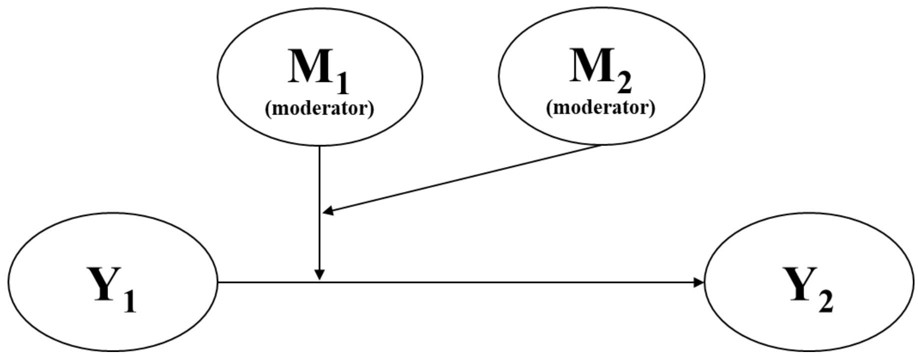
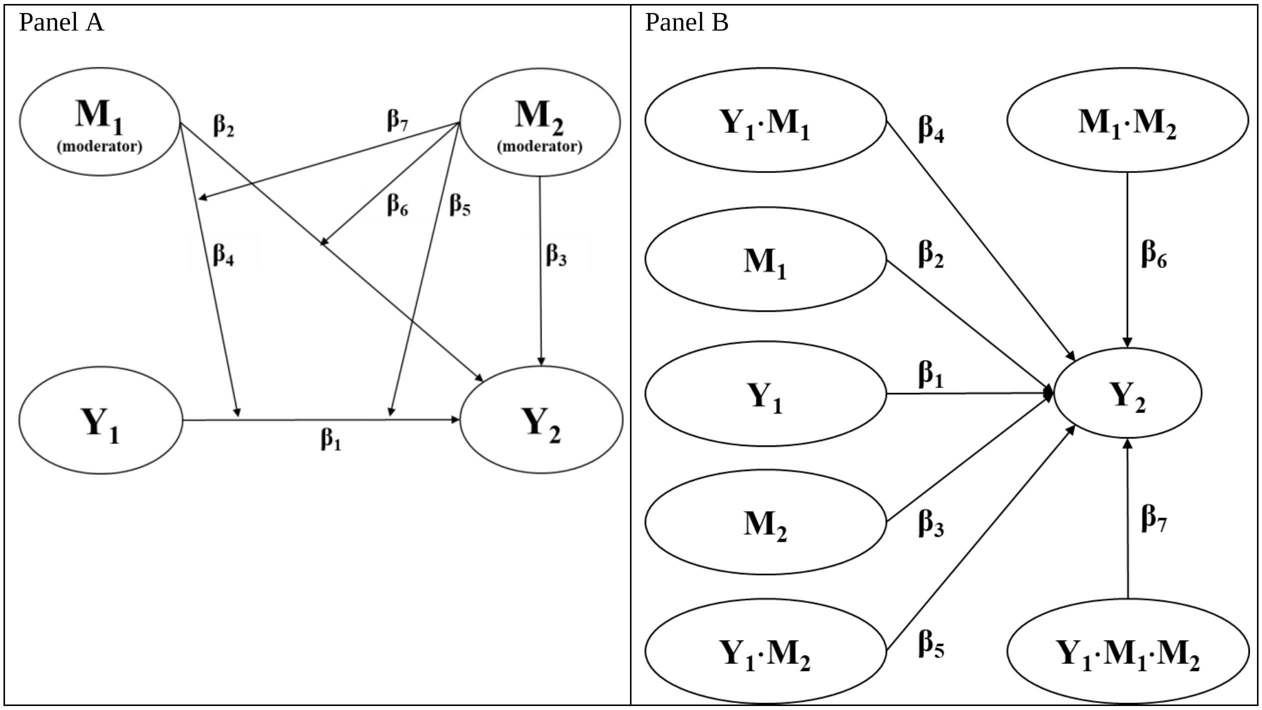


Figure 5. Theoretical model of a moderated moderation (i.e., three-way interaction)



Note: The figure was adopted in a modified version from Henseler (2021, Chap. 11).

Figure 6. Statistical model of three-way interaction

Tables

Table 1. Estimation mode of the higher-order construct

Repeated indicators approach, extended repeated indicators approach, and first stage of the embedded two-stage approach	
Type of higher-order model	**Estimation mode of the higher-order construct**
Reflective-reflective (Type I)	Mode A
Reflective-formative (Type II)	Mode B
Formative-reflective (Type III)	Mode A
Formative-formative (Type IV)	Mode B

Table 2. PLS-SEM results of the room type moderation model.

Standardizing the binary variable	
Relationship	**Path Coefficient**
Customer Satisfaction → Customer Loyalty	0.5017
Room Type → Customer Loyalty	-0.0040
Room Type → Customer Satisfaction → Customer Loyalty	-0.0216
Corrected results	
Relationship	**Path Coefficient**
Customer Satisfaction → Customer Loyalty *(for Room Type = Standard)*	0.5303
Room Type → Customer Loyalty	-0.0084
Room Type → Customer Satisfaction → Customer Loyalty	-0.0449

Table 3. Overview

Bootstrapping	
Question	*Considerations*
What kind of bootstrap confidence interval method should be used?	Use the (nonparametric) percentile bootstrapping method. In case of a highly asymmetric parameter distribution (e.g., after graphical inspection of a coefficient's bootstrap distribution), apply the bias-corrected and accelerated bootstrapping (BCa) approach.
What is the sample size per bootstrap subsample?	The sample size per bootstrap subsample should be equal to the number of observations used for estimating the model. This also holds for group-specific analyses.
How many bootstrap subsamples should be used?	The more the better. But as some point out, additional computations only marginally improve the bootstrap distribution and might not justify the additional computations and the time they require. While initial model estimations can draw on a smaller number of bootstrap subsamples (e.g., 1,000), the final analysis should use at least 10,000 subsamples
Which significance level should be chosen and should the effect sizes be interpreted?	Researchers should consider the trade-off between type I and type II errors in their research setting and choose the significance level accordingly. The main strategy to avoid type II error is to use enough observations to achieve high power. Thus, researchers should perform a power analysis before conducting a study. Any p-values barely below the chosen significance level should not be taken as strong evidence in favor of an effect. Researchers should also consider the effect sizes, particularly when dealing with interaction terms.
Higher-order constructs	
Question	*Considerations*
When should one use higher-order constructs?	Use higher-order constructs – to estimate theoretically established constructs of this type in the model, – to overcome the bandwidth-fidelity dilemma, and – to address collinearity issues. Consider only theoretically established higher-order constructs (i.e., those resulting from scale development). Use the lower-order constructs directly in a model when no established higher-order construct is available.
How can higher-order models be specified?	Based on theoretical assumptions, researchers should include appropriate types of higher-order models in their research, such as reflective-reflective (Type I), reflective-formative (Type II), formative-reflective (Type III), and formative-formative (Type IV) models.
How should higher-order models be estimated?	Use the embedded two-stage approach or the disjoint two-stage approach. In case of using the embedded two-stage approach, make sure in the first stage that the reflective-formative (Type II) and formative-formative (Type IV) higher-order model estimation in PLS-SEM uses Mode B for the higher-order construct (Mode A otherwise). Include the LOC scores of the first stage as indicators of the HOC in the second stage (and keep the measurement models of the other constructs as they are).
How should higher-order models be assessed?	Use the PLS-SEM evaluation criteria for the LOCs in the first stage and do not include the HOC in this evaluation. In the second stage, the LOCs become the indicators of the HOC. Assess this HOC measurement model along with all other measurement models and the structural model by applying the usual evaluation criteria for PLS-SEM.
Moderation	
Question	*Considerations*
Should the model be analyzed with or without the moderator included?	To answer this question, the following three scenarios need to be distinguished:

	(1) The aim of the study is to test the moderating effect, while the direct effect that is being moderated is not subject to hypothesis testing. (2) The aim of the study is to test the moderating effect as well as the direct effect that is being moderated. (3) The aim of the study is not to test a moderating effect, but rather to investigate ex post facto whether the direct effect is stable or depends on certain contextual factors (which are theoretically plausible, but not an explicit part of a model or theory). This analysis is also often discussed as a robustness check. In the first scenario, only the full model that includes the moderator and interaction term should be analyzed. In the second scenario, researchers should assess the direct effect in a base model without interaction term and then the full model with the moderator included, while acknowledging the limitations of the base model resulting from potential heterogeneity if the interaction is significant. In the last scenario, it is also advisable to first analyze the model without moderation (i.e., the hypothesized research model) and perform additional moderation analyses in the next step.
How should the interaction term be generated?	Researchers should rely on the two-stage approach to generate the interaction term's measurement model. The resulting product should not be standardized, and the researchers should estimate and interpret the unstandardized coefficient.
How should binary moderators be used?	To obtain estimates that are interpretable, one should take the binary variable's standardization into account and do a manual correction: (1) Researchers need to determine the standard deviation change that is implied by a change in category (e.g., a switch from standard to premium room type). (2) Researchers need to correct the standardized coefficient by multiplying with this number, because we are not interested in a standard deviation change (that has no meaning on a binary variable), but in the category change. (3) Researchers need to determine the correct conditional effects of the focal predictor (e.g., satisfaction) at both moderator levels.
How should a three-way interaction analysis be conducted?	As with two-way interactions, researchers should draw on the two-stage approach to estimate models with three-way interactions. The resulting product should not be standardized, and the researchers should estimate and interpret the unstandardized coefficient.

PLS-SEM's most wanted guidance

Authors' short bio

Jan-Michael Becker is an associate professor at the Department of Marketing, BI Norwegian Business School. He has received his doctoral degree from the University of Cologne in Germany, where he also worked as a postdoctoral researcher and lecturer in Marketing. His research interest focuses on the digital transformation of marketing and consumer behavior as well as marketing analytics, behavioral research methods, and computational statistics. His research has been published in several premier academic journals, including *Information Systems Research, MIS Quarterly, Journal of the Academy of Marketing Science, International Journal of Research in Marketing, Psychometrika, Multivariate Behavioral Research,* and *Nature Human Behaviour*. He is a co-founder of the SmartPLS software application.

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Christian M. Ringle is a chaired professor of management at the Hamburg University of Technology, Germany. His research addresses human resource management, organization, marketing, strategic management, and quantitative methods for business and market research. His articles have been published in journals such as the *Information Systems Research, International Journal of Human Resource Management, International Journal of Research in Marketing, Journal of the Academy of Marketing Science, Organizational Research Methods,* and *MIS Quarterly*. Since 2018, he has been included in the Clarivate Analytics' Highly Cited Researchers list. He is also one of the SmartPLS founders. More information about Dr. Ringle can be found at https://www.tuhh.de/hrmo/team/prof-dr-c-m-ringle.html

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