Industrial Marketing Management 128 (2025) 1–9

Contents lists available at ScienceDirect

Industrial Marketing Management

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

PLS-SEM and reflective constructs: A response to recent criticism and a constructive path forward

Peter Guenther[a,*], Miriam Guenther[a], Christian M. Ringle[b], Ghasem Zaefarian[c], Severina Cartwright[a]

[a] Management School, University of Liverpool, Liverpool, UK
[b] Department of Management Sciences and Technology, Hamburg University of Technology, Germany, and James Cook University, Australia
[c] Leeds University Business School, University of Leeds, Leeds, UK

ARTICLE INFO

Keywords:
Partial least squares
Structural equation modeling
PLS-SEM
Common factors
Composites
Components
Reflective constructs
Multimethod

ABSTRACT

This article addresses criticisms asserting that reflective construct measurement and its associated evaluation criteria are unsuitable for partial least squares structural equation modeling (PLS-SEM). More specifically, critics contend that reflective measurement models correspond exclusively to common factor models, a premise that is both inaccurate and misleading. Reflective measurement models represent theoretically grounded and conceptualized constructs. Statistical methods such as common factor model estimation, composite model estimation, and sum score regression enable researchers to estimate method-specific proxies that serve as approximations for theoretically established conceptual constructs in empirical research. These proxies vary depending on the statistical models and assumptions inherent to each method. In this context, it is important to highlight that the use of reflective evaluation criteria is not restricted to common factor models. When applied to composite model estimation, it does not compromise the validity of the results. Moreover, this article advocates for embracing the complementary strengths of diverse SEM methods within a multimethod approach, rather than positioning one method in opposition to another. We believe that this contribution provides critical insights and guidance, fostering advancements in SEM methodology, and its practical applications.

1. Introduction

We thank the editors-in-chief of *Industrial Marketing Management (IMM)*, Anthony Di Benedetto and Adam Lindgreen, for accepting and publishing our article titled "Improving PLS-SEM use for business marketing research" (Guenther et al., 2023). Our article provides business marketing researchers with practical, up-to-date guidance on when and how to use the partial least squares structural equation modeling (PLS-SEM; Lohmöller, 1989; Wold, 1982) approach while also addressing common errors observed in previous applications. Additionally, it explores advanced analytical techniques that researchers and practitioners can employ to gain deeper insights, thereby enhancing the contributions of their research projects. The article's rapid emergence as one of the most cited *IMM* publications underscores its relevance and the critical issues it addresses in a widely used research methodology. The recently published *IMM* article by Cabanelas et al. (2025) indicates, for instance, that "particularly Partial Least Squares (PLS-SEM or variance-based SEM) are among the most applied techniques in B2B marketing" (p. 72).[1]

We also thank the *IMM* editors for inviting us to respond to the

* Corresponding author.
E-mail address: Peter.Guenther@liverpool.ac.uk (P. Guenther).

[1] We thank an anonymous reviewer for highlighting the adoption of PLS-SEM in research methods courses for doctoral students over the past two decades. See also the reviews of PLS-SEM use in marketing research (e.g., Guenther et al., 2023; Hair, Sarstedt, Ringle, & Mena, 2012; Henseler et al., 2009; Sarstedt et al., 2022) and across a wide range of disciplines (e.g., management, medicine, engineering, psychology, political and environmental sciences); for an overview of PLS-SEM review studies across different disciplines, see Table 1 in Cepeda-Carrión et al. (2022); also see Table 1.1 in Hair et al. (2021). In this context, it is noteworthy that researchers have made significant progress in improving and extending the capabilities of the PLS-SEM method, and in overcoming its limitations, as called for in earlier publications (e.g., McIntosh et al., 2014). For instance, Table 1 in Gudergan et al. (2025) provides an overview of methodological advancements in PLS-SEM. These advancements have significantly expanded the method's capabilities and strengthened its role as a key method for multivariate analyses across business research and various other disciplines.

https://doi.org/10.1016/j.indmarman.2025.05.003
Received 29 January 2025; Received in revised form 13 May 2025; Accepted 14 May 2025
Available online 19 May 2025
0019-8501/

commentary by Henseler et al. (2025) to foster a constructive dialogue in their journal.[2] Henseler et al. (2025) present two main arguments: 1) PLS-SEM is unsuitable for estimating reflectively measured constructs because it produces biased parameter estimates, and 2) the assessment criteria for evaluating reflective measurement models are also biased. Based on these claims, the critics argue that our guidance on using PLS-SEM for reflective measurement models is misguided. In the following, we explain why their concerns are unwarranted.

2. Reflective measurement does not equal common factor models

Henseler et al.'s (2025) critique is based on the assumption that reflective measurement models are equivalent to common factor models. They therefore conclude that estimating reflectively specified measurement models inevitably needs to draw on the covariance-based structural equation modeling (CB-SEM; Jöreskog, 1978) approach with its different estimators (e.g., Boomsma & Hoogland, 2001; Shi & Maydeu-Olivares, 2020),[3] or on composite-based SEM methods that are adjusted to mimic outcomes under the assumption that the data stem from a common factor model, such as PLSe-SEM (Huang, 2013), consistent PLS-SEM (PLSc-SEM; Dijkstra, 2014), the GSCA$_M$ (Hwang et al., 2017) version of the generalized structured component analysis (GSCA; Hwang & Takane, 2004), and integrated GSCA (IGSCA; Hwang et al., 2021).[4] As plausible as this argument may seem at first, this assumption and all the resulting conclusions are built on quicksand.

Over the last few decades, researchers have gone to considerable lengths to distinguish between model design and model estimation (e.g., Cook & Forzani, 2023; Rhemtulla et al., 2020; Rigdon, 2012). Building on Bagozzi and Phillips (1982) holistic construal (see also Bagozzi, 1984, 2011; Bagozzi & Phillips, 1982; Bagozzi & Yi, 2012), Rigdon (2012) developed the concept of a proxy framework, which differentiates between conceptual variables—that is, the proxies representing these conceptual variables in statistical models (i.e., the constructs)—and the indicators, which are linked to the proxies through mathematical operations (Fig. 1). Rigdon (2012) uses this framework to highlight the validity gap between the proxy and the concept, a notion that other researchers also raised (Rossiter, 2002, 2011a, 2011b).

> Recognizing the distinction between concept and proxy means recognizing the actual steps and the actual difficulties in measuring theoretical concepts. The theoretical concept remains idealized and out of reach … the question of measurement validity is not about the links between indicators and proxies – these are mere mathematical operations, with no causal significance. Instead, measurement validity questions center on the similarity in behavior between each proxy and the theoretical concept for which it stands.
> Rigdon (2012, p. 348).

Follow-up research has identified this validity gap as metrological uncertainty (e.g., Rigdon et al., 2020; Rigdon & Sarstedt, 2022), which is a quantifiable parameter that characterizes the range within which a measured quantity's true value is assumed to lie, as based on the measurement process, the instruments used, and the environmental conditions (JCGM, 2012). This uncertainty impacts all of the research process's elements (i.e., the concept, the proxy, and the observed variables; Rigdon & Sarstedt, 2022), thereby underlining the notion that *any* measurement is just an approximation of the underlying concept (Cliff, 1983; Rossiter, 2002; Stanley & Spence, 2024). Rigdon et al. (2019a) have shown that this notion even holds under a perfect model fit when uncertainty causes a misalignment between the conceptual variable and the common factor.

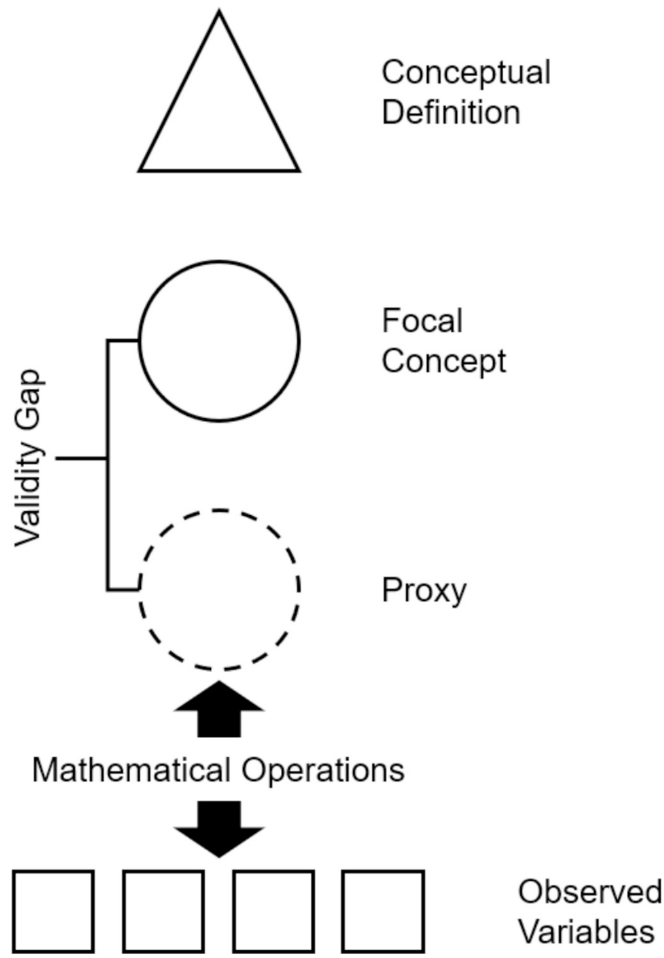

Fig. 1. Concept proxy framework (adapted from Rigdon, 2012, p. 347).

Drawing on a proxy framework, Sarstedt et al. (2016) differentiate the measurement models' conceptualization and operationalization from the data-generation process. These authors emphasize that the decision to operationalize a construct reflectively or formatively is solely and exclusively a conceptual one grounded in measurement theory. This is also reflected in the manifold guidelines that facilitate identifying how to specify a measurement model, which usually build on conceptual arguments related to the indicator correlations (e.g., Jarvis et al., 2003). This measurement-theoretic layer needs to be distinguished from the data-generation process underlying the model, which could follow common factor logic or composite model logic. The data-generation process can differ from measurement-theoretical assumptions. For example, measurement-theoretic arguments might favor a reflective specification, which highly correlated indicators that meet common reliability and validity standards support, although the underlying data might stem from a composite model—as in Hair et al.'s (2017) comparative evaluation of composite-based SEM estimators.

Indicators in a measurement model might be conceptually (and empirically) highly correlated, giving rise to a reflective specification, even if the mental model underlying the respondents' answering behavior might follow a composite logic. The latter is due to any attitude

[2] Note: In their *IMM* commentary, Henseler et al. (2025) repeat some of the key arguments that Henseler et al. (2024) previously published in *Electronic Commerce Research*. This response can therefore also be regarded as a partial response to that earlier article.

[3] Different CB-SEM estimation methods include, for example, maximum likelihood (ML), generalized least squares (GLS), the asymptotically distribution-free (ADF) estimator, unweighted least squares (ULS), weighted least squares (WLS), and diagonally weighted least squares (DWLS).

[4] In line with, for instance, Hwang et al. (2020) and Sarstedt et al. (2024), we use the terms composites and components interchangeably in this research.

expressed at a particular point in time being the result of a constructive process (Zaller & Feldman, 1992). Rather than reflecting a single, fixed attitude toward an object or issue, attitudes are flexible, real-time constructs based on accessible information, current emotional states, and contextual cues (e.g., Fazio et al., 1984; Regan & Fazio, 1977; Stern et al., 1995). Hence, there is no compelling argument for composites not representing concepts, although they still yield highly correlated indicators that adhere to reflective measurement model standards.

The difference between a measurement theory and a data-generating process also becomes evident when using formative measurement models in CB-SEM (e.g., Bollen & Diamantopoulos, 2017; Diamantopoulos & Winklhofer, 2001; Rigdon et al., 2014; Treiblmaier et al., 2011). These models' estimation follows a common factor model logic, regardless of whether the researcher assumes causal or composite indicators, thereby underscoring the notion that theory-based model specification (i.e., formative) and model estimation (common factor estimation) are two distinct research process elements.

Unlike this notion, Henseler et al.'s (2025) perspective encompasses that high indicator correlations imply the presence of a common factor model, while weakly correlated indicators suggest the presence of a composite model if the corresponding model holds in the population. In other words, Henseler et al. (2025) view SEM use as a purely statistical practice that essentially lacks all measurement-theoretic conceptual considerations. However, determining the best way of measuring a concept and choosing an estimator are two distinct tasks that, while conceptually related, need to be treated separately.

Metrology—the scientific study of measurement—acknowledges that measurement cannot capture the data-generating process perfectly, and that measurement is, to some extent, inherently subjective (Rigdon et al., 2020; Rigdon & Sarstedt, 2022). In the context of psychometrics, this distinction underscores that determining the best way of measuring a concept and of choosing an estimator are two distinct tasks. Rigdon, Sarstedt, and Ringle (2017, p. 7) explore the reasons for this confusion by noting,

> "researchers' functional background and adherence to a specific position in philosophy of science contribute to the confusion over which method is 'right' and which one is 'wrong.'"

While we acknowledge that researchers with a strong background in statistics are influenced by their beliefs, the world is more complex than the simulation studies they rely on, and which shape their specific worldview (e.g., Koivisto, 2017; Pawel et al., 2024). Furthermore, we recognize that researchers like Henseler et al. (2025) might be uncomfortable with the notion that the underlying data-generating process, which remains unknown in SEM methods' real-world applications, cannot be straightforwardly linked to the measurement model specification.

Given these complexities, the more pressing question is: What happens if my assumptions about the data-generating process are wrong? Sarstedt et al. (2016) explore this issue and find that when PLS-SEM is incorrect about how the world really works (i.e., the data-generating process), the resulting consequences are less severe than those arising from a similar incorrectness in CB-SEM.[5] Specifically, these authors find that, on average, the bias, which factor-based SEM produces, can be 11 times higher than the bias that PLS-SEM produces when each method is applied to models inconsistent with their underlying assumptions (i.e., factor-based SEM applied to composite models, and PLS-SEM to common factor models). Cho, Sarstedt, and Hwang (2022) confirmed these findings by using a more comprehensive model design. Their results show that the mean absolute error in path coefficient estimates is nearly twice as high when using CB-SEM to estimate composite models than when using PLS-SEM to estimate common factor models. Based on this evidence, we concur with Sarstedt et al. (2016, p. 263) that,

> "PLS-SEM seems to be the safer choice … when the underlying model type [i.e., the data-generating process] is unknown."

In this context, it is also worth mentioning the finding of Deng and Yuan (2023, p. 1475) who conclude that.

> "the estimates of the path coefficients under CB-SEM may contain sizable sampling errors due to simultaneously estimating many parameters. In practice, the substantive interests are often prediction and/or classification of individuals. Then path analysis with composite scores has the advantage of directly estimating the relationship of the observed scores."

3. On the assessment of reflectively measured constructs

We have already elaborated that Henseler et al.'s (2025) assumption that reflective measures are equivalent to common factor models is conceptually hard to defend. However, for the sake of the argument, let us assume that their critique might actually be valid. What would the consequences for measurement model results be? Further, what would the consequences for measurement model validation be?

In PLS-SEM, assessing reflectively measured constructs typically includes the indicator reliability (i.e., based on the squared standardized loadings), the internal consistency reliability (i.e., using Cronbach's α, composite reliability ρ_C, reliability coefficient ρ_A), the convergent reliability (i.e., based on the average variance extracted, AVE), and discriminant validity (i.e., using the HTMT criterion)—see, for example, Chin (1998); Hair, Hult, Ringle, and Sarstedt (2022, Chapter 4); Ringle et al. (2023). Which of these criteria would actually be adversely affected by the alleged 'inflated' loadings resulting from 'erroneously' estimating reflective measurement models with PLS-SEM?

The HTMT criterion's computation does not use the loadings, and is, therefore, identical for both CB-SEM and PLS-SEM. In order to assess the internal consistency reliability, the PLS-SEM literature recognizes that Cronbach's α, which does not rely on loadings for its computation (and thus yields identical results for CB-SEM and PLS-SEM), is too conservative, while the composite reliability ρ_C metric, which incorporates the loadings in its computation, is too liberal (e.g., Dijkstra & Henseler, 2015b; Guenther et al., 2023; Sarstedt et al., 2021). The reliability coefficient ρ_A (Dijkstra & Henseler, 2015b) serves as the preferred metric between the previous two internal consistency reliability measures (e.g., Hair et al., 2022, Chapter 4; Sarstedt et al., 2021). Since ρ_A does not rely on indicator loadings, the alleged mismatch between PLS-SEM and the reflective measurement model estimation likewise does not affect it. In fact, the only metrics affected by loadings, which are assumed to be somewhat inflated, are the indicator reliability (i.e., the squared standardized PLS-SEM loadings) and the AVE, which averages each construct's indicator reliabilities. 'Inflated' means that PLS-SEM provides slightly higher loadings than CB-SEM when assuming data from a common factor model population, because PLS-SEM, unlike CB-SEM, does not divide the variance into common and unique variance (Guenther et al., 2023; Sarstedt et al., 2016). PLS-SEM might therefore also return higher AVE results.

According to common guidelines, the AVE should exceed 0.50, suggesting that, on average, the construct explains more than 50 % of its indicators. If the indicator loadings are indeed inflated due to the application of PLS-SEM to common factor models, there is a concern that researchers might interpret estimates from models that actually lack

[5] We thank an anonymous reviewer, and adopt the suggestion to include the following clarification: The discussion of the data-generating process is closely tied to the treatment of proxies and conceptual definitions, as explained by Rigdon (2012) and illustrated in Figure 1. To make this connection more explicit–particularly (e.g., when referring to Sarstedt et al., 2016 and measurement and model estimation framework as displayed in their Figure 3)–it is important to emphasize that, in the context of establishing reflective constructs, "conceptual" indeed refers to the theoretical layer. This is consistent with the notion of a measurement-theoretic layer.

convergent validity, as the true AVE values might fall below the 0.50 threshold.

Prior studies that estimated common factor models using PLS-SEM help to assess the extent and severity of inflated loadings. For instance, Cho, Sarstedt, and Hwang (2022) analyzed common factor- and composite-based SEM methods' performance, reporting an average mean absolute error of 0.074 in the loadings when using PLS-SEM to estimate common factor models.[6] The error is higher (> 0.1) for measurement models with three indicators, but decreases notably when the sample size increases. Further, Schuberth, Hubona, et al. (2023) present the results of a similar analysis with less complexity. Their results parallel those of Cho et al. (2022), showing that in common factor models, PLS-SEM-based loadings are approximately 0.1 units higher when the measurement model has *three* indicators. This is a relatively small number of indicators, and the difference diminishes as the number of indicators and sample size increase, due to PLS-SEM's consistency at large characteristic (Hui & Wold, 1982; Schneeweiß, 1993)—see, for example, Reinartz et al. (2009); Sarstedt et al. (2016). In an empirical case study involving constructs with three to five indicators, Dash and Paul (2021) compared CB-SEM and PLS-SEM estimates, reporting loadings differences ranging from 0.00 to 0.08, with an average difference of 0.05. These results suggest that even under the inadmissible assumption that reflective measurement models are equivalent to common factor models, the extent to which PLS-SEM inflates loading estimates is not substantial. Nevertheless, in the following, we explore what such inflation would mean for published PLS-SEM studies.

We tackled the issue by revisiting Sarstedt et al.'s (2022) review of PLS-SEM use in the top-30 marketing journals between 2011 and 2020. In total, these authors identified 239 articles applying PLS-SEM to estimate and analyze 486 models (i.e., 38.91 % of the articles report two or more alternative models or different datasets). The authors of the corresponding articles reported an average of 3.85 indicators per reflective construct and documented 1825 AVE values. The analysis reveals that the average AVE value across all the models is 0.722, with a minimum value of 0.330, and a maximum value of 0.995. The distribution depicted in Fig. 2 shows that the vast majority of AVE values are substantially larger than 0.5. Fig. 2 also presents the percentiles of all AVE values extracted from Sarstedt et al. (2022). A detailed examination indicates that, when assuming an average loading inflation of 0.05 units, as in Dash and Paul (2021), 87 % of all constructs would still achieve convergent validity if the AVE threshold is adjusted to 0.573, reflecting a correction factor of 0.05 added to the common loading threshold of 0.707.

Jointly, these results suggest that the claim that PLS-SEM is unsuitable for reflective measurement model validation is vastly exaggerated. This holds particularly because it is well-known that the differences between PLS-SEM and CB-SEM estimates diminish as the number of indicators and the sample size increase, when the data-generating process adheres to the statistical common factor model (consistency at large characteristic; Hui & Wold, 1982; Schneeweiß, 1993). Also,

> "simulation studies show that the differences between PLS-SEM and CB-SEM estimates when assuming the latter as a standard of comparison are very small, provided that measurement models meet minimum recommended standards in terms of measurement quality (i.e., reliability and validity). Specifically, when the measurement models have four or more indicators and indicator loadings meet the common standards (≥0.70), there is practically no difference between the two methods in terms of parameter accuracy …".
> (Hair et al., 2022, p. 23).

Consequently, measurement model validation based on metrics that build on indicator loadings, is unlikely to yield different conclusions in

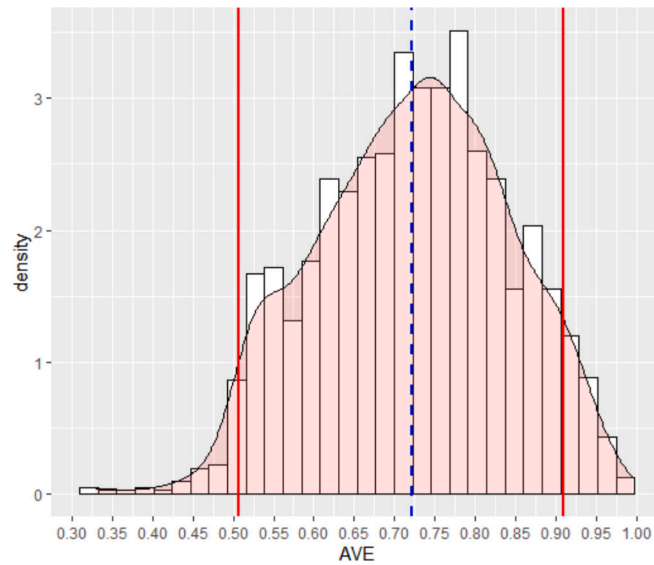

Fig. 2. Average variance extracted (AVE) value distribution.
Note: The figure shows the AVE value distribution, the density function, the mean value (dashed vertical line), and the 2.5 % / 97.5 % percentiles (solid vertical lines).

situations commonly encountered in the methods' real-world applications.

The extant literature has long documented all of this; it is therefore particularly surprising that Henseler et al. (2025) raise this issue again, given that Hair et al. (2024a) recently refuted similar criticism by Rönkkö et al. (2023). Based on a series of empirical studies, Rönkkö et al. (2023) argued that the AVE is unsuitable for detecting measurement model misspecification. Hair et al. (2024a), however, demonstrated that this critique is based on the selective reporting of statistics, and on reliance on outdated guidelines to validate PLS-SEM-based measurement models. Using the full range of metrics identifies model misspecification in practically all instances. Given these results, Hair et al. (2024a, p. 94) conclude that,

> "[n]ot surprisingly, if one searches hard enough, one will always find model misspecifications that do not raise a red flag and likely leaves any substantiation based on measurement theory considerations aside."

4. Key takeaways

4.1. Measurement theoretical model ≠ statistical estimation

Researchers of various scientific disciplines have recognized that common factor models are often not an ideal approach for measuring concepts (e.g., Cho, Sarstedt, & Hwang, 2022; Rhemtulla et al., 2020; Rigdon et al., 2019a; Rigdon et al., 2019b), and argue that they rarely hold in applied research (e.g., Atinc et al., 2012; Schönemann & Wang, 1972). In addition, research has shown that common factor models could be subject to considerable degrees of metrological uncertainty, which has serious consequences for their validity (Rigdon et al., 2020; Rigdon & Sarstedt, 2022). Substantial doubt about the common factor model's universal appropriateness and applicability raises the question of why researchers consider common factors the gold standard for estimating constructs (Hair & Sarstedt, 2019; Sarstedt et al., 2023). In keeping with Hair, Sarstedt, and Ringle (2019, p. 571), we argue that they should not.

> "In fact, numerous researchers have warned against reflex-like adherence to the common factor model … with recent research

[6] Note that the MAE in loadings that CB-SEM produces when used to estimate composite models is 0.101, thus 36 % higher than when using PLS-SEM to estimate common factor models.

suggesting that composites may actually capture a conceptual variable more accurately than a common factor can."

And as Yuan and Zhang (2024, p. 8) highlight:

"But we admit that there always exist differences between theoretical constructs and the latent variables in practice. Although the setup implicitly favors latent variable models, as was typically done in the field, we will discuss the rationale and provide the evidence that regression analysis with weighted composites yields different but more efficient parameter estimates than SEM instead of biased estimates."

Most importantly, a construct's theoretically conceptualized reflective measurement *does not equal* estimating a common factor model by means of empirical data. Henseler et al. (2025) believe the opposite, thereby imposing critical and widely limiting assumptions on SEM, which the literature has repeatedly challenged and refuted (e.g., Cook & Forzani, 2023; Rhemtulla et al., 2020; Rigdon, 2012; Rigdon et al., 2017). This is also reflected in Reinartz et al. (2009, p. 334), who note that,

"CBSEM and PLS analysis are essentially two different approaches to the same problem. Both start from the same set of theoretical and measurement equations but differ in how they approach the parameter estimation problem."

SEM is by far not the only field in which researchers distinguish between a theoretically established conceptual model and a statistical one (e.g., Collins, 2006; Lubell et al., 2012; McCullagh, 2002). An example of this is a moderator of a standard regression analysis assuming that a third variable impacts the strength or even the direction of two variables' relationship (e.g., Aguinis et al., 2017; Dawson, 2014). In a conceptual model, an arrow pointing at the relationship between two variables represents this assumed relationship. To translate this conceptual model into a statistical model, researchers need to include an auxiliary variable that takes the moderator and the independent variables' interaction into account (i.e., to facilitate an analysis of the interaction effects). In regression models with moderation, researchers therefore need to clearly distinguish between a theoretically established conceptual model and a statistical one (e.g., Fairchild & MacKinnon, 2009; Helm & Mark, 2012); the same applies to PLS-SEM's moderator analysis (e.g., Becker et al., 2023; Henseler, 2021, Chapter 11). Similarly, researchers distinguish between conceptual and statistical models in their mediation analysis and in their moderated mediation analysis (e.g., Liu et al., 2022). Consequently, conceptual and statistical models are two different elements of the research process.

4.2. SEM is a toolkit of methods, none of which is inherently invalid

We also emphasize that model estimation by means of empirical data and a specific method with its underlying statistical model and requirements, which are often not perfectly met in empirical studies, ultimately produces proxies. There is, however, a validity gap between the proxies and the conceptual variables (e.g., Rigdon, 2012; Sarstedt et al., 2016). Quantifying the validity gap is a highly challenging task (Rigdon et al., 2020). Researchers never know with absolute certainty whether the data stem from a common factor model or a composite model population. They cannot therefore determine with certainty, which model estimation method (e.g., common factor, composite model, equal weights or sumscores) has the lowest validity gap. Researchers have, however, repeatedly demonstrated that the bias resulting from using PLS-SEM when estimating common factor models (i.e., in simulation studies with artificially generated data for common factor models) is generally trivial (e.g., Reinartz et al., 2009; Sarstedt et al., 2016), and substantially smaller than the bias produced when using CB-SEM to estimate composite models (Cho et al., 2023; Sarstedt et al., 2016). Consequently, PLS-SEM seems to be the safer choice when the underlying model type is unknown. Rigdon's (2024) findings substantiate this conclusion further by demonstrating that regression component analysis (RCA) and regression-weighted forms of PLS-SEM and GSCA are all consistent approaches for modeling data that conform to a factor model (see also McDonald, 1996).[7]

"While these methods—RCA, PLS path modeling and GSCA—do model relations between composites, one can better think of them as quasi-factor methods. RCA, in particular, starts with a factor model … an updated method for constructing data sets consistent with the GSCA model [that] relies on factor model-like covariance structures. The label 'quasi-factor methods' better captures this relationship." Rigdon (2023, p. 30).

Accordingly, researchers could use alternative methods to estimate reflectively operationalized conceptual variables. These methods include, for instance, CB-SEM with its large variety of alternative model estimation methods (e.g., ML, GLS, ADF, ULS), PLS-SEM, PLSc-SEM/PLSe-SEM, GSCA, IGSCA, factor score regression offering various techniques to compute the factor scores, and sum score regression (based, e.g., on unstandardized or standardized indicator data). To some extent, these approaches consider different statistical models, different model estimation algorithms as well as their specific requirements. They therefore produce different statistical results that adhere to the same conceptual model. In their multimethod SEM example, Sarstedt et al. (2024) do not only demonstrate the differences in the statistical results obtained from five different SEM methods for the same conceptual model, but also highlight the impact of the researchers' analytical decisions on these outcomes.

5. A constructive path forward

Given the inherent uncertainty in real-life data settings about the data-generating process and the optimal methodology, adopting a complementary perspective (methods A *and* B) rather than a mutually exclusive stance (A *or* B) seems more prudent. Suggestions that one method should always be preferred over the other are likely to be ill-advised, as such preferences rely on assumptions about unknown elements of the model and the data (Rigdon et al., 2017). Instead, researchers should just acknowledge this methodological uncertainty (Sarstedt et al., 2024, p. 1109).

As a constructive way forward when using SEM in studies, we recommend that business marketing researchers consider the different methods as tools within a methodological toolbox, and adopt a multimethod SEM approach. From this perspective, any potential sensitivity to method choices is an inherent part of the academic discourse on a given phenomenon across studies (e.g., Campa & Kedia, 2002; Whited, 2001). Robustness tests could also be used to examine sensitivities within a single study. Researchers using a composite-based SEM approach could confirm their findings' robustness by also estimating the model with a common factor-based method, and vice versa.

"One has room to appreciate regression component analysis, generalized structured component analysis, and PLS path modeling as valuable analytical methods. Not being common factor methods does not make them flawed—rather, it enables them to avoid an important shortcoming of the factor analytic approach. The dominance of

[7] It is worth noting that a comparison with common factor results could also be achieved by using PLS-SEM approaches that mimic common factor model estimation and/or outcomes. For instance, Dijkstra (2014) introduced consistent PLS-SEM (see also Dijkstra & Henseler, 2015b; Dijkstra & Schermelleh-Engel, 2014). Similarly, Huang (2013) provided an approach that mimics CB-SEM outcomes by using PLS-SEM results (see also Bentler & Huang, 2014). In addition, when using GSCA (Hwang & Takane, 2004) for composite model estimations, researchers could use IGSCA (Hwang et al., 2021) to mimic CB-SEM outcomes (Cho, Schlägel, Hwang, Choi, Sarstedt, & Ringle, 2022c; Hwang et al., 2021; Hwang et al., 2023).

common factor-based SEM can make it hard to appreciate the merits, and even the exact nature, of alternative procedures, but effective researchers will keep an open mind."
Rigdon (2023, p. 31).

When adopting a multimethod approach to SEM, we advise business marketing researchers to focus on the robustness of the inferences rather than the differences in estimation results across methods. Such differences are to be expected when estimating models with empirical data, for the following three main reasons: (1) Alternative methods, such as CB-SEM with its various estimators (e.g., ML, GLS, ADF, ULS) and PLS-SEM, employ different statistical models to estimate SEM's theoretically conceptualized models; (2) empirical data often contain imperfections and, to some extent, violate methodological requirements, which potentially biases the results; (3) each method's application involves numerous decisions during the analysis process, each of which could influence the final results to varying degrees. Even though the results are not identical across the various methods, we also expect to see notable differences between the different CB-SEM estimators (e.g., Boomsma & Hoogland, 2001; Shi & Maydeu-Olivares, 2020) or when using sum score regression (Hair et al., 2024b), but not between ML-CBSEM, PLS-SEM, PLSc-SEM/PLSe-SEM, GSCA, and IGSCA when considering reflectively measured constructs (Cho, Sarstedt, & Hwang, 2022; Dijkstra & Henseler, 2015b; Reinartz et al., 2009; Sarstedt et al., 2016). The situation changes, however, when formatively measured constructs from a composite population are assumed. In this case, researchers are advised to use PLS-SEM or GSCA (Cho et al., 2023; Hair et al., 2017; Sarstedt et al., 2016).

A multimethod approach to SEM allows researchers to assess whether their findings and conclusions are consistent across methods (e.g., both CB-SEM and PLS-SEM identify the same coefficient as the strongest compared to the others). Alternatively, differences in the outcomes across methods prompt researchers to investigate and determine whether (1) the theoretical model requires refinement, (2) there are issues and problems with the data used, or (3) whether certain of the employed statistical methods' technical specifics lead to unexpected outcomes or are violated requirements—or even whether a combination of these three considerations is responsible for the differences.

Furthermore, a multimethod approach allows researchers to address alternative SEM objectives by employing specific techniques. CB-SEM, for instance, allows the model to be assessed as a whole (e.g., by applying model fit criteria; Hayduk et al., 2007; Zhang et al., 2021). A high model fit ensures that the theoretical model and real-world observations are aligned (e.g., Bentler, 1990; Browne & Cudeck, 1992; Hu & Bentler, 1999; McNeish & Wolf, 2023; Niemand & Mai, 2018).[8] In contrast, PLS-SEM facilitates the evaluation of a model's out-of-sample predictive capabilities (e.g., by using PLSpredict and CVPAT; Liengaard et al., 2021; Sharma et al., 2023; Shmueli et al., 2016; Shmueli et al., 2019).[9] Given the predictive nature of results on which managerial recommendations are based, demonstrating a theoretically established model's predictive power is highly critical from a practical viewpoint (Hair, 2021; Hair & Sarstedt, 2021). Similarly, Deng and Yuan (2023) recommend that researchers should begin their model analysis by using CB-SEM, followed by PLS-SEM (or related methods). This allows researchers to take advantage of important measurement and modeling features that CB-SEM offers (e.g., the reliability of individual items and the overall model structure's goodness of fit), while benefitting from the advantages of PLS-SEM, which, as Deng and Yuan (2023) show, offers a higher signal-to-noise ratio and superior performance in prediction, classification and individual-level diagnosis (see also Yuan & Zhang, 2024).

In conclusion, combining both methods in a multimethod approach to SEM enables PLS-SEM researchers to benefit, for instance, from CB-SEM-based model fit assessment, thereby ensuring that the theoretical model aligns well with real-world observations based on empirical data. Conversely, CB-SEM researchers can leverage PLS-SEM's capabilities to demonstrate the model's predictive power. This is essential for supporting management recommendations drawn from research findings, which are inherently forward-looking. Moreover, CB-SEM researchers can use the PLS-SEM results, which are often more robust due to the method's less restrictive requirements, to identify issues in their model specification and estimation (i.e., when the results differ widely), especially when they arise from violations of CB-SEM requirements and assumptions.[10] Finally, a multimethod approach to SEM might reduce the methodological, model estimation, and interpretational uncertainty—as outlined by Sarstedt et al. (2024)—by mitigating the risks associated with relying on a single method throughout the model estimation process.

A multimethod approach to SEM would also open new avenues for future research, offering opportunities to overcome past conflicts between method-specific viewpoints; for example, by integrating both exploratory and confirmatory research approaches within a unified framework and addressing methodological uncertainties through a multimethod approach (Sharma et al., 2024). Key areas for future research include distinguishing between conceptual and statistical models, defining and estimating the constructs (e.g., reflective, causal, formative, and others), evaluating them with appropriate criteria and flexible cut-off values, combining model fit and predictive power assessment, and assessing the validity gap between theoretically established conceptual constructs and their statistically derived proxies (i.e., as obtained through different SEM methods). To facilitate advancements that build on empirical research, researchers should be aware of and adapt open science initiatives (Deer, Adler, Datta, Mizik, & Sarstedt, 2024; Wagenmakers et al., 2021) that aim to foster research (Adler et al., 2023; Sharma et al., 2024).

6. Conclusion

In conclusion, we reject Henseler et al.'s (2025) criticism because their fundamental assumption—that the theoretically conceptualized reflective measurement of constructs is equivalent to common factor model estimation using empirical data—is incorrect. This perspective has been repeatedly challenged and refuted in the literature (e.g., Cook

[8] Note: Before PLS-SEM is applied to perform other analyses that require PLS-SEM construct scores (and/or that are not possible in CB-SEM) and to determine the predictive power of the model, CB-SEM can be used to ensure model fit, among other things. To properly execute CB-SEM, researchers usually employ a relatively large data set to meet the CB-SEM requirements. At the same time, a high model fit is often associated with high indicator loadings (i.e., usually notably higher then 0.7). In this case, the CB-SEM results are very similar to the PLS-SEM results due to the consistency at large condition, and not much remains of the problems that Henseler et al. (2025) describe.

[9] Note that, to some extent, PLS-SEM and PLSc-SEM/PLSe-SEM support the assessment of both model fit (Dijkstra & Henseler, 2015a; Henseler, Dijkstra, Sarstedt, Ringle, Diamantopoulos, Straub, Ketchen, Hair, Hult, & Calantone, 2014; Schuberth, Rademaker, & Henseler, 2023) and predictive power (Sharma et al., 2023; Shmueli et al., 2016; Shmueli et al., 2019). GSCA and IGSCA similarly support the assessment of both model fit (e.g., Cho et al., 2020; Cho et al., 2022c) and predictive power (Cho et al., 2019; Cho et al., 2023; Cho, Hwang, Sarstedt, & Ringle, 2022a).

[10] We thank an anonymous reviewer for suggesting the inclusion of this important aspect concerning model estimation, particularly when different methods are involved. Although the consistency–robustness trade-off in PLS-SEM has been extensively debated in the literature, it is worthwhile to revisit this issue. For example, Cassel et al. (1999) emphasize a practical perspective by examining the effects of skewness, multicollinearity, and model misspecification across various data-generating processes. Their findings suggest that while extreme skewness can introduce bias, PLS-SEM generally remains both robust and consistent under typical conditions (see also, for example, Hair et al., 2017; Sarstedt et al., 2016).

& Forzani, 2023; Rhemtulla et al., 2020; Rigdon, 2012; Rigdon et al., 2017), and common factor models are not the undisputed gold standard for estimating constructs (Hair & Sarstedt, 2019; Sarstedt et al., 2023). Even if one were to accept that Henseler et al.'s (2025) assumption is reasonable, the consequences of its violation are trivial.

We also conclude that the methodological debate should not devolve into an "either-or" dichotomy, but instead embrace a "both-and" perspective—supporting recent calls for a multimethod approach to SEM (e.g., Sarstedt et al., 2024; Sharma et al., 2024)—and advocate for the combined use of SEM methods, including CB-SEM (with its different estimators, e.g., ML, GLS, ADF, ULS), PLS-SEM, PLSc-SEM/PLSe-SEM, GSCA, and IGSCA. This practice transcends superficial pro-and-con method debates, reinforces the original complementary perspective of SEM methods as envisioned by their originators (Jöreskog & Wold, 1982), and aligns with recent PLS-SEM literature emphasizing this view (e.g., Binz Astrachan et al., 2014; Dash & Paul, 2021; Hair, Sarstedt, Pieper, & Ringle, 2012; Richter et al., 2022; Riou et al., 2015). All SEM-based research will benefit from these suggestions, since a multimethod approach to SEM not only allows researchers to confirm their results' robustness across different methods, to eliminate methodological uncertainties, but also ensures their results' quality across different criteria (e.g., model fit and the model's predictive relevance) and helps researchers pursue a combination of different research objectives (e.g., in both exploratory and confirmatory research).

In conclusion, we reject the premise that PLS-SEM is inherently flawed for use with reflective measurement models. Instead, we advocate for methodological pluralism and encourage researchers to prioritize the substantive contributions of their models over pedantic critiques of estimation methods. The true test of any research methodology lies in its ability to generate meaningful, actionable insights—an objective that PLS-SEM has consistently achieved. Let us channel our collective efforts toward refining and applying SEM methods to tackle the pressing methodological challenges faced across disciplines. The way forward is not in entrenching ourselves in rigid methodological positions, but in collaborating to advance methodological innovation and scientific rigor.

CRediT authorship contribution statement

Peter Guenther: Writing – review & editing, Writing – original draft, Project administration, Investigation, Conceptualization. **Miriam Guenther:** Writing – review & editing, Writing – original draft, Conceptualization. **Christian M. Ringle:** Writing – review & editing, Writing – original draft, Conceptualization, Methodology, Validation. **Ghasem Zaefarian:** Writing – review & editing. **Severina Cartwright:** Writing – review & editing.

Acknowledgement

Even though this research does not use the statistical software SmartPLS (https://www.smartpls.com), Christian M. Ringle acknowledges a financial interest in SmartPLS.

Data availability

No data was used for the research described in the article.

References

Adler, S. J., Sharma, P. N., & Radomir, L. (2023). Toward Open Science in PLS-SEM: Assessing the state of the art and future perspectives. *Journal of Business Research, 169*, Article 114291.

Aguinis, H., Edwards, J. R., & Bradley, K. J. (2017). Improving our understanding of moderation and mediation in strategic management research. *Organizational Research Methods, 20*(4), 665–685.

Atinc, G., Simmering, M. J., & Kroll, M. J. (2012). Control variable use and reporting in macro and Micro management research. *Organizational Research Methods, 15*(1), 57–74.

Bagozzi, R. P. (1984). A prospectus for theory construction in marketing. *Journal of Marketing, 48*(1), 11–29.

Bagozzi, R. P. (2011). Measurement and meaning in information systems and organizational research: Methodological and philosophical foundations. *MIS Quarterly, 35*(2), 261–292.

Bagozzi, R. P., & Phillips, L. W. (1982). Representing and testing organizational theories: A holistic construal. *Administrative Science Quarterly, 27*(3), 459–489.

Bagozzi, R. P., & Yi, Y. (2012). Specification, evaluation, and interpretation of structural equation models. *Journal of the Academy of Marketing Science, 40*(1), 8–34.

Becker, J.-M., Cheah, J. H., Gholamzade, R., Ringle, C. M., & Sarstedt, M. (2023). PLS-SEM'S Most wanted guidance. *International Journal of Contemporary Hospitality Management, 35*(1), 321–346.

Bentler, P. M. (1990). Comparative fit indices in structural models. *Psychological Bulletin, 107*(2), 238–246.

Bentler, P. M., & Huang, W. (2014). On components, latent variables, PLS and simple methods: Reactions to Rigdon's rethinking of PLS. *Long Range Planning, 47*(3), 138–145.

Binz Astrachan, C., Patel, V. K., & Wanzenried, G. (2014). A comparative study of CB-SEM and PLS-SEM for theory development in family firm research. *Journal of Family Business Strategy, 5*(1), 116–128.

Bollen, K. A., & Diamantopoulos, A. (2017). In Defense of Causal–Formative Indicators: A Minority Report. *Psychological Methods, 22*(3), 581–596.

Boomsma, A., & Hoogland, J. J. (2001). The robustness of LISREL modeling revisited. In R. Cudeck, S. du Toit, & D. Sörbom (Eds.), *Structural equation modeling: Present and future* (pp. 139–168). Chicago: Scientific Software International.

Browne, M. W., & Cudeck, R. (1992). Alternative ways of assessing model fit. *Sociological Methods & Research, 21*(2), 230–258.

Cabanelas, P., Mora Cortez, R., Pérez-Moure, H., & Lampón, J. F. (2025). Sampling and sample size in B2B marketing: Current practices and recommendations. *Industrial Marketing Management, 125*, 71–86.

Campa, J. M., & Kedia, S. (2002). Explaining the diversification discount. *The Journal of Finance, 57*(4), 1731–1762.

Cassel, C., Hackl, P., & Westlund, A. H. (1999). Robustness of partial least-squares method for estimating latent variable quality structures. *Journal of Applied Statistics, 26*(4), 435–446.

Cepeda-Carrión, G., Hair, J. F., Ringle, C. M., Roldán, J. L., & García-Fernández, J. (2022). Guest editorial: Sports management research using partial least squares structural equation modeling (PLS-SEM). *International Journal of Sports Marketing and Sponsorship, 23*(2), 229–240.

Chin, W. W. (1998). The partial least squares approach to structural equation modeling. In G. A. Marcoulides (Ed.), *Modern methods for business research* (pp. 295–358). Mahwah, NJ: Lawrence Erlbaum.

Cho, G., Hwang, H., Sarstedt, M., & Ringle, C. M. (2020). Cutoff criteria for overall model fit indexes in generalized structured component analysis. *Journal of Marketing Analytics, 8*, 189–202.

Cho, G., Hwang, H., Sarstedt, M., & Ringle, C. M. (2022). A prediction-oriented specification search algorithm for generalized structured component analysis. *Structural Equation Modeling: A Multidisciplinary Journal, 29*(4), 611–619.

Cho, G., Jung, K., & Hwang, H. (2019). Out-of-bag prediction error: A cross validation index for generalized structured component analysis. *Multivariate Behavioral Research, 54*(4), 505–513.

Cho, G., Lee, J., Hwang, H., Sarstedt, M., & Ringle, C. M. (2023). A comparative study of the predictive power of component-based approaches to structural equation modeling. *European Journal of Marketing, 57*(6), 1641–1661.

Cho, G., Sarstedt, M., & Hwang, H. (2022). A comparative evaluation of factor- and component-based structural equation modelling approaches under (in)correct construct representations. *British Journal of Mathematical and Statistical Psychology, 75*(2), 220–251.

Cho, G., Schlägel, C., Hwang, H., Choi, Y., Sarstedt, M., & Ringle, C. M. (2022). Integrated generalized structured component analysis: On the use of model fit criteria in international management research. *Management International Review, 62*, 569–609.

Cliff, N. (1983). Some cautions concerning the application of causal modeling methods. *Multivariate Behavioral Research, 18*(1), 115–126.

Collins, L. M. (2006). Analysis of longitudinal data: The integration of theoretical model, temporal design, and statistical model. *Annual Review of Psychology, 57*, 505–528.

Cook, D. R., & Forzani, L. (2023). On the role of partial least squares in path analysis for the social sciences. *Journal of Business Research, 167*, Article 114132.

Dash, G., & Paul, J. (2021). CB-SEM vs PLS-SEM methods for research in social sciences and technology forecasting. *Technological Forecasting and Social Change, 173*, Article 121092.

Dawson, J. F. (2014). Moderation in management research: What, why, when, and how. *Journal of Business and Psychology, 29*(1), 1–19.

Deer, L., Adler, S., Datta, H., Mizik, N., & Sarstedt, M. (2024). Toward Open Science in marketing research. *International Journal of Research in Marketing, 42*(1), 212–233.

Deng, L., & Yuan, K.-H. (2023). Which method is more powerful in testing the relationship of theoretical constructs? A Meta comparison of structural equation modeling and path analysis with weighted composites. *Behavior Research Methods, 76*(3), 646–678.

Diamantopoulos, A., & Winklhofer, H. M. (2001). Index construction with formative indicators: An alternative to scale development. *Journal of Marketing Research, 38*(2), 269–277.

Dijkstra, T. K. (2014). PLS' Janus Face – Response to Professor Rigdon's 'Rethinking Partial Least Squares Modeling: In Praise of Simple Methods'. *Long Range Planning, 47*(3), 146–153.

Dijkstra, T. K., & Henseler, J. (2015a). Consistent and asymptotically Normal PLS estimators for linear structural equations. *Computational Statistics & Data Analysis, 81*(1), 10–23.

Dijkstra, T. K., & Henseler, J. (2015b). Consistent partial least squares path modeling. *MIS Quarterly, 39*(2), 297–316.

Dijkstra, T. K., & Schermelleh-Engel, K. (2014). Consistent partial least squares for nonlinear structural equation models. *Psychometrika, 79*(4), 585–604.

Fairchild, A. J., & MacKinnon, D. P. (2009). A general model for testing mediation and moderation effects. *Prevention Science, 10*(2), 87–99.

Fazio, R. H., Lenn, T. M., & Effrein, E. A. (1984). Spontaneous Attitude Formation. *Social Cognition, 2*(3), 217–234.

Gudergan, S. P., Moisescu, O. I., Radomir, L., Ringle, C. M., & Sarstedt, M. (2025). Special issue editorial: Advanced partial least squares structural equation modeling (PLS-SEM) applications in business research. *Journal of Business Research, 188*, 115087.

Guenther, P., Guenther, M., Ringle, C. M., Zaefarian, G., & Cartwright, S. (2023). Improving PLS-SEM use for business marketing research. *Industrial Marketing Management, 111*(May), 127–142.

Hair, J. F. (2021). Next generation prediction metrics for composite-based PLS-SEM. *Industrial Management & Data Systems, 121*(1), 5–11.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3 ed.). Thousand Oaks, CA: Sage.

Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). *Partial least squares structural equation modeling (PLS-SEM) using R*. Cham: Springer.

Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., & Thiele, K. O. (2017). Mirror, Mirror on the wall: A comparative evaluation of composite-based structural equation modeling methods. *Journal of the Academy of Marketing Science, 45*(5), 616–632.

Hair, J. F., & Sarstedt, M. (2019). Factors versus composites: Guidelines for choosing the right structural equation modeling method. *Project Management Journal, 50*(6), 619–624.

Hair, J. F., & Sarstedt, M. (2021). Explanation plus prediction: The logical focus of Project Management research. *Project Management Journal, 52*(4), 319–322.

Hair, J. F., Sarstedt, M., Pieper, T. M., & Ringle, C. M. (2012). The use of partial least squares structural equation modeling in strategic management research: A review of past practices and recommendations for future applications. *Long Range Planning, 45*(5–6), 320–340.

Hair, J. F., Sarstedt, M., & Ringle, C. M. (2019). Rethinking some of the rethinking of partial least squares. *European Journal of Marketing, 53*(4), 566–584.

Hair, J. F., Sarstedt, M., Ringle, C. M., & Mena, J. A. (2012). An assessment of the use of partial least squares structural equation modeling in marketing research. *Journal of the Academy of Marketing Science, 40*(3), 414–433.

Hair, J. F., Sarstedt, M., Ringle, C. M., Sharma, P. N., & Liengaard, B. D. (2024a). Going beyond the untold facts in PLS-SEM and moving forward. *European Journal of Marketing, 58*(13), 81–106.

Hair, J. F., Sarstedt, M., Ringle, C. M., Sharma, P. N., & Liengaard, B. D. (2024b). The shortcomings of equal weights estimation and the composite equivalence index in PLS-SEM. *European Journal of Marketing, 58*(13), 30–55.

Hayduk, L., Cummings, G., Boadu, K., Pazderka-Robinson, H., & Boulianne, S. (2007). Testing! Testing! One, two, three – Testing the theory in structural equation models! *Personality and Individual Differences, 42*(5), 841–850.

Helm, R., & Mark, A. (2012). Analysis and evaluation of moderator effects in regression models: State of art, alternatives and empirical example. *Review of Managerial Science, 6*(4), 307–332.

Henseler, J. (2021). *Composite-based structural equation modeling: Analyzing latent and emergent variables*. New York, NY: Guilford Press.

Henseler, J., Lee, N., Roemer, E., Kemény, I., Dirsehan, T., & Cadogan, J. W. (2024). Beware of the Woozle effect and belief perseverance in the PLS-SEM literature! *Electronic Commerce Research, 24*, 715–774.

Henseler, J., Ringle, C. M., & Sinkovics, R. R. (2009). The use of partial least squares path modeling in international marketing. In R. R. Sinkovics, & P. N. Ghauri (Eds.)*, Vol. 20. Advances in international marketing* (pp. 277–320). Emerald: Bingley.

Henseler, J., Schuberth, F., Lee, N., & Kemény, I. (2025). *Why researchers should be cautious about using PLS-SEM*. Industrial Marketing Management. Forthcoming.

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal, 6*(1), 1–55.

Huang, W. (2013). *PLSe: Efficient estimators and tests for partial Least Square (dissertation)*. Los Angeles, CA: University of California Los Angeles.

Hui, B. S., & Wold, H. (1982). Consistency and consistency at large of partial least squares estimates. In K. G. Jöreskog, & H. Wold (Eds.), *Systems under indirect observation, part II* (pp. 119–130). Amsterdam: North Holland.

Hwang, H., Cho, G., Jung, K., Falk, C. F., Flake, J. K., Jin, M. J., & Lee, S. H. (2021). An approach to structural equation modeling with both factors and components: Integrated generalized structured component analysis. *Psychological Methods, 26*(3), 273–294.

Hwang, H., Sarstedt, M., Cheah, J. H., & Ringle, C. M. (2020). A concept analysis of methodological research on composite-based structural equation modeling: Bridging PLSPM and GSCA. *Behaviormetrika, 47*, 219–241.

Hwang, H., Sarstedt, M., Cho, G., Choo, H., & Ringle, C. M. (2023). A primer on integrated generalized structured component analysis. *European Business Review, 35*(3), 261–284.

Hwang, H., & Takane, Y. (2004). Generalized structured component analysis. *Psychometrika, 69*(1), 81–99.

Hwang, H., Takane, Y., & Jung, K. (2017). Generalized structured component analysis with uniqueness terms for accommodating measurement error. *Frontiers in Psychology, 8*.

Jarvis, C. B., MacKenzie, S. B., & Podsakoff, P. M. (2003). A critical review of construct indicators and measurement model misspecification in marketing and consumer research. *Journal of Consumer Research, 30*(2), 199–218.

JCGM. (2012). *International vocabulary of metrology—Basic and general concepts and associated terms (VIM)* (3 ed.). JCGM.

Jöreskog, K. G. (1978). Structural analysis of covariance and correlation matrices. *Psychometrika, 43*(4), 443–477.

Jöreskog, K. G., & Wold, H. (1982). The ML and PLS techniques for modeling with latent variables: Historical and comparative aspects. In K. G. Jöreskog, & H. Wold (Eds.), *Systems under indirect observation, part I* (pp. 263–270). Amsterdam: North-Holland.

Koivisto, M. (2017). Pitfalls in modeling and simulation. *Procedia Computer Science, 119*, 8–15.

Liengaard, B. D., Sharma, P. N., Hult, G. T. M., Jensen, M. B., Sarstedt, M., Hair, J. F., & Ringle, C. M. (2021). Prediction: Coveted, yet forsaken? Introducing a cross-validated predictive ability test in partial least squares path modeling. *Decision Sciences, 52*(2), 362–392.

Liu, H., Yuan, K.-H., & Wen, Z. (2022). Two-level moderated mediation models with single-level data and new measures of effect sizes. *Behavior Research Methods, 54*(2), 574–596.

Lohmöller, J.-B. (1989). *Latent variable path modeling with partial least squares*. Heidelberg: Physica.

Lubell, M., Scholz, J., Berardo, R., & Robins, G. (2012). Testing policy theory with statistical models of networks. *Policy Studies Journal, 40*(3), 351–374.

McCullagh, P. (2002). What is a statistical model? *The Annals of Statistics, 30*(5), 1225–1310, 1286.

McDonald, R. P. (1996). Path analysis with composite variables. *Multivariate Behavioral Research, 31*(2), 239–270.

McIntosh, C. N., Edwards, J. R., & Antonakis, J. (2014). Reflections on partial least squares path modeling. *Organizational Research Methods, 17*(2), 210–251.

McNeish, D., & Wolf, M. G. (2023). Dynamic fit index cutoffs for confirmatory factor analysis models. *Psychological Methods, 28*, 61–88.

Niemand, T., & Mai, R. (2018). Flexible cutoff values for fit indices in the evaluation of structural equation models. *Journal of the Academy of Marketing Science, 46*(6), 1148–1172.

Pawel, S., Kook, L., & Reeve, K. (2024). Pitfalls and potentials in simulation studies: Questionable research practices in comparative simulation studies allow for spurious claims of superiority of any method. *Biometrical Journal, 66*(1), 2200091.

Regan, D. T., & Fazio, R. (1977). On the consistency between attitudes and behavior: Look to the method of attitude formation. *Journal of Experimental Social Psychology, 13*(1), 28–45.

Reinartz, W. J., Haenlein, M., & Henseler, J. (2009). An empirical comparison of the efficacy of covariance-based and variance-based SEM. *International Journal of Research in Marketing, 26*(4), 332–344.

Rhemtulla, M., van Bork, R., & Borsboom, D. (2020). Worse than measurement error: Consequences of inappropriate latent variable measurement models. *Psychological Methods, 25*(1), 30–45.

Richter, N. F., Hauff, S., Ringle, C. M., & Gudergan, S. P. (2022). The use of partial least squares structural equation modeling and complementary methods in international management research. *Management International Review, 62*, 449–470.

Rigdon, E. E. (2012). Rethinking Partial Least Squares Path Modeling: In Praise of Simple Methods. *Long Range Planning, 45*(5–6), 341–358.

Rigdon, E. E. (2023). Needed developments in the understanding of quasi factor methods. *Communications of the Association for Information Systems, 52*, 692–696.

Rigdon, E. E. (2024). Understanding composite-based structural equation modeling methods from the perspective of regression component analysis. *Multivariate Behavioral Research, 59*(4), 677–692.

Rigdon, E. E., Becker, J.-M., Rai, A., Ringle, C. M., Diamantopoulos, A., Karahanna, E., … Dijkstra, T. K. (2014). Conflating antecedents and formative indicators: A comment on Aguirre-Urreta and Marakas. *Information Systems Research, 25*(4), 780–784.

Rigdon, E. E., Becker, J.-M., & Sarstedt, M. (2019a). Factor indeterminacy as metrological uncertainty: Implications for advancing psychological measurement. *Multivariate Behavioral Research, 54*(3), 429–443.

Rigdon, E. E., Becker, J.-M., & Sarstedt, M. (2019b). Parceling cannot reduce factor indeterminacy in factor analysis: A research note. *Psychometrika, 84*(3), 772–780.

Rigdon, E. E., & Sarstedt, M. (2022). Accounting for uncertainty in the measurement of unobservable marketing phenomena. In H. Baumgartner, & B. Weijters (Eds.)*, Vol. 19. Review of marketing research: Measurement in marketing* (pp. 53–73). Emerald: Bingley.

Rigdon, E. E., Sarstedt, M., & Becker, J.-M. (2020). Quantify uncertainty in behavioral research. *Nature Human Behaviour, 4*, 329–331.

Rigdon, E. E., Sarstedt, M., & Ringle, C. M. (2017). On comparing Results from CB-SEM and PLS-SEM. Five Perspectives and Five Recommendations. *Marketing ZFP, 39*(3), 4–16.

Ringle, C. M., Sarstedt, M., Sinkovics, N., & Sinkovics, R. R. (2023). A perspective on using partial least squares structural equation modelling in data articles. *Data in Brief, 48*, Article 109074.

Riou, J., Guyon, H., & Falissard, B. (2015). An introduction to the partial least squares approach to structural equation modelling: A method for exploratory psychiatric research. *International Journal of Methods in Psychiatric Research*, n/a-n/a.

Rönkkö, M., Lee, N., Evermann, J., McIntosh, C. N., & Antonakis, J. (2023). Marketing or methodology? Exposing fallacies of PLS with simple demonstrations. *European Journal of Marketing, 57*(6), 1597–1617.

Rossiter, J. R. (2002). The C-OAR-SE procedure for scale development in marketing. *International Journal of Research in Marketing, 19*(4), 305–335.

Rossiter, J. R. (2011a). Marketing measurement revolution: The C-OAR-SE method and why it must replace psychometrics. *European Journal of Marketing, 45*(11/12), 1561–1588.

Rossiter, J. R. (2011b). *Measurement for the social sciences: The C-OAR-SE method and why it must replace psychometrics*. New York, NY: Springer.

Sarstedt, M., Adler, S. J., Ringle, C. M., Cho, G., Diamantopoulos, A., Hwang, H., & Liengaard, B. D. (2024). Same model, same data, but different outcomes: Evaluating the impact of method choices in structural equation modeling. *Journal of Product Innovation Management, 41*(6), 1100–1117.

Sarstedt, M., Hair, J. F., Pick, M., Liengaard, B. D., Radomir, L., & Ringle, C. M. (2022). Progress in partial least squares structural equation modeling use in marketing research in the last decade. *Psychology & Marketing, 39*(5), 1035–1064.

Sarstedt, M., Hair, J. F., & Ringle, C. M. (2023). "PLS-SEM: Indeed a silver bullet" – Retrospective observations and recent advances. *Journal of Marketing Theory & Practice, 31*(3), 261–275.

Sarstedt, M., Hair, J. F., Ringle, C. M., Thiele, K. O., & Gudergan, S. P. (2016). Estimation issues with PLS and CBSEM: Where the Bias lies! *Journal of Business Research, 69*(10), 3998–4010.

Sarstedt, M., Ringle, C. M., & Hair, J. F. (2021). Partial least squares structural equation modeling. In C. Homburg, M. Klarmann, & A. E. Vomberg (Eds.), *Handbook of market research* (pp. 1–47). Cham: Springer.

Schneeweiß, H. (1993). Consistency at large in models with latent variables. In K. Haagen, D. J. Bartholomew, & M. Deistler (Eds.), *Statistical modelling and latent variables* (pp. 299–320). Amsterdam: Elsevier.

Schönemann, P. H., & Wang, M.-M. (1972). Some new results on factor indeterminacy. [journal article]. *Psychometrika, 37*(1), 61–91.

Schuberth, F., Hubona, G., Roemer, E., Zaza, S., Schamberger, T., Chuah, F., … Henseler, J. (2023). The choice of structural equation modeling technique matters: A commentary on Dash and Paul (2021). *Technological Forecasting and Social Change, 194*, Article 122665.

Schuberth, F., Rademaker, M. E., & Henseler, J. (2023). Assessing the overall fit of composite models estimated by partial least squares path modeling. *European Journal of Marketing, 57*(6), 1678–1702.

Sharma, P. N., Liengaard, B. D., Hair, J. F., Sarstedt, M., & Ringle, C. M. (2023). Predictive model assessment and selection in composite-based modeling using PLS-SEM: Extensions and guidelines for using CVPAT. *European Journal of Marketing, 57*(6), 1662–1677.

Sharma, P. N., Sarstedt, M., Ringle, C. M., Cheah, J.-H., Herfurth, A., & Hair, J. F. (2024). A framework for enhancing the replicability of behavioral MIS research using prediction oriented techniques. *International Journal of Information Management, 78*, Article 102805.

Shi, D., & Maydeu-Olivares, A. (2020). The effect of estimation methods on SEM fit indices. *Educational and Psychological Measurement, 80*(3), 421–445.

Shmueli, G., Ray, S., Velasquez Estrada, J. M., & Chatla, S. B. (2016). The elephant in the room: Evaluating the predictive performance of PLS models. *Journal of Business Research, 69*(10), 4552–4564.

Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: Guidelines for using PLSpredict. *European Journal of Marketing, 53*(11), 2322–2347.

Stanley, D. J., & Spence, J. R. (2024). The comedy of measurement errors: Standard error of measurement and standard error of estimation. *Advances in Methods and Practices in Psychological Science, 7*(4), 25152459241285885.

Stern, P. C., Kalof, L., Dietz, T., & Guagnano, G. A. (1995). Values, beliefs, and Proenvironmental action: Attitude formation toward emergent attitude objects. *Journal of Applied Social Psychology, 25*(18), 1611–1636.

Treiblmaier, H., Bentler, P. M., & Mair, P. (2011). Formative constructs implemented via common factors. *Structural Equation Modeling: A Multidisciplinary Journal, 18*(1), 1–17.

Wagenmakers, E.-J., Sarafoglou, A., Aarts, S., Albers, C., Algermissen, J., Bahník, Š., … Aczel, B. (2021). Seven steps toward more transparency in statistical practice. *Nature Human Behaviour, 5*(11), 1473–1480.

Whited, T. M. (2001). Is it inefficient investment that causes the diversification discount? *The Journal of Finance, 56*(5), 1667–1691.

Wold, H. (1982). Soft modeling: The basic design and some extensions. In K. G. Jöreskog, & H. Wold (Eds.), *Systems under indirect observations: Part II* (pp. 1–54). Amsterdam: North-Holland.

Yuan, K.-H., & Zhang, Z. (2024). Modeling data with measurement errors but without predefined metrics: Fact versus fallacy. *Journal of Behavioral Data Science, 4*(2), 1–28.

Zaller, J., & Feldman, S. (1992). A simple theory of the survey response: Answering questions versus revealing preferences. *American Journal of Political Science, 35*(3), 579–616.

Zhang, M. F., Dawson, J. F., & Kline, R. B. (2021). Evaluating the use of covariance-based structural equation modelling with reflective measurement in organizational and management research: A review and recommendations for best practice. *British Journal of Management, 32*(2), 257–272.