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**Reflexões e tendências**

# Second order constructs in applications of partial least squares structural equation modeling: how to specify, estimate and validate

*Construtos de segunda ordem em modelagem de equações estruturais com mínimos quadrados parciais: como especificar, estimar e avaliar*

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## 1 INTRODUCTION

Many variables in business studies have been conceptualized in a multidimensional way. In other words, numerous variables have been conceptualized as constructs composed of a comprehensive, higher-order conceptual dimension involving lower-order conceptual sub-dimensions. Corporate governance of non-governmental organizations (e.g., Lacruz, Nossa, Lemos & Guedes, 2021), corporate reputation (e.g., Schwaiger, 2004), and organizational structure (Trigueiro-Fernandes, Cavalcanti, Bila & Añez, 2022) are examples of variables conceptualized in a multidimensional way.

In this context, Partial Least Squares Structural Equation Modeling (PLS-SEM) has been used to model multidimensional constructs, such as the management control system (e.g., Pazetto & Beuren, 2022), the intention to engage (e.g., Aslam & Luna, 2021) or entrepreneurial behavior (e.g., Campos, Moraes & Spatti, 2021), for example.

Research in the field of Accounting that explores latent phenomena, like those tied to perceptions, motivations, and attitudes, such as in Behavioral Accounting (e.g., Lau & Roopnarain, 2014), or composite measures, like corporate performance and management information systems (e.g., Nicolaou, Sedatole & Lankton, 2011), finds a valuable tool in the PLS-SEM technique for data analysis. This approach enables the investigation of models incorporating multidimensional concepts and structures with multiple direct and indirect relationships (between exogenous and endogenous variables). Importantly, it avoids potential bias from simultaneous equations, which arises when explanatory variables are correlated with the error term in simultaneous equation models.

These multidimensional constructs are usually called higher-order models or hierarchical component models, according to Lohmöller (1989). We will remain consistent with the acronym PLS-SEM and the term hierarchical component models.

In PLS-SEM, latent variables are treated considering that the concepts examined can be measured as composite variables, assumed to represent theoretical concepts. Therefore, in PLS-SEM, the variables are regarded as representations of the constructs; thus, they are taken as proxies (variables used to replace another that is difficult to measure) of the conceptual variables.

With the increasing use of the technique, researchers inexperienced with this method experience difficulties (Becker, Cheah, Gholamzade, Ringle & Sarstedt, 2022). Therefore, review studies on PLS-SEM highlight several incorrect applications, particularly when involving more complex tasks (Sarstedt, Hair Jr., Pick, Liengaard, Radomir & Ringle, 2022; Sarstedt, Radomir, Moisescu & Ringle, 2022). These misuses are problematic, as they contribute to the perpetuation of practices that have already been notably criticized (Sarstedt, Hair Jr. & Ringle, 2022).

To contextualize the scenario (i.e., without the intention of addressing an in-depth analysis), in a survey of all 2021 editions of the core national periodicals in the area of "Public and Business Administration, Accounting Sciences and Tourism", classified as A2 in Qualis/Capes, it was observed that in all articles it was possible to

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identify the specification of the lower order component (e.g., reflexively specified) and the relationship between the higher-order component and the lower-order components (e.g., formative relationship). However, in some articles, it was impossible to identify the approach used to specify the higher-order component (e.g., repeated measures approach), nor was the evaluation of the higher-order component demonstrated. Furthermore, no article identified the technique used to estimate the latent variables (i.e., the weighting scheme of the internal approximation step of the PLS-SEM algorithm).

A review by Becker et al. (2022) aligns with these findings. The authors identified the topic of hierarchical component models as one of the main points of doubt among users of the technique. Even with the evolution of the PLS-SEM technique, most users seem to be unaware of recent guidelines and recommendations (Sarstedt, Hair Jr., Pick et al., 2022; Sarstedt, Ringle, Cheah, Ting, Moisescu & Radomir, 2020).

In the area of Accounting, in particular, we see the recurrence of reported problems, which can be a significant disruption in replicating methods and results. For example, Lopes, Meurer, and Voese (2018), who analyzed the effect of self-efficacy beliefs on the citizen and counterproductive behavior of accounting academics, use second-order constructs. It was impossible to identify the relationship between the higher-order component and the lower-order components, the specification of the lower-order components, or the approach used to specify the higher-order component; moreover, the evaluation of the lower-order constructs and higher were not made separately.

Pazetto and Beuren (2022), who analyzed the influence of the design of management control systems on inter-organizational cooperation and the moderating role of identifying companies with their technological park, bring the approach used to specify the higher-order component. However, it was unattainable to identify the specification of the lower order components, the relationship between the higher order and lower order components, or the technique used to estimate the latent variables. Furthermore, the lower and higher-order constructs were not assessed separately.

Hierarchical component models, as they involve more than one conceptual dimension, must have the higher-order component evaluated separately – in addition to the lower-order components. This implies the appropriate specification, estimation, and evaluation of hierarchical component models, as different approaches for estimating the higher order component and/or the way of measuring this component and/or internal weighting scheme produce different results (Becker, Klein & Wetzels, 2012).

Despite studies dedicated to studying how to properly use hierarchical component models (e.g., Wetzels, Odekerken-Schröder & Oppen, 2009; Becker et al., 2012; Ringle, Sarstedt & Straub, 2012; Sarstedt, Hair Jr., Cheah, Becker & Ringle, 2019; Crocetta, Antonucci, Cataldo, Galasso, Grassia, Lauro & Marino, 2021), the effort to organize and synthesize clear guidelines on which configuration is most appropriate for each type of hierarchical component model is justified – considering the inadequacy of the way of reporting how the studies were executed, observed in the survey carried out in this study and previous studies (e.g., Ringle et al., 2012).

With this in mind, this article provides thorough guidance on the technical aspects of employing hierarchical component models in PLS-SEM, focusing specifically on second-order constructs. Regarding aspects related to the operational definition of the conceptual variable in hierarchical component models, it is recommended to know the synthesis offered by Hair Jr., Sarstedt, Ringle, and Gudergan (2018, p. 41-47). Nevertheless, it only covers some of the notes brought here.

This study is expected to contribute to a better understanding of how to specify, estimate, evaluate and report the results of hierarchical component models. This analytical effort is not a comparison between existing approaches. Instead, it constitutes a guide for those who work or intend to work with PLS-SEM using models with second-order constructs.

## 2 HIERARCHICAL COMPONENT MODELS

Hierarchical component models allow modeling constructions on a dimension considered more abstract and more concrete subdimensions (Wetzels et al., 2009). Thus, hierarchical models have two elements: the higher-order components, at the most abstract level, and the lower-order components, which involve the subdimensions of the higher-order (Hair Jr., Hult, Ringle & Sarstedt, 2017, 2022).

In this way, hierarchical constructions can be defined as constructions that involve more than one dimension and can reach different ramifications (third, fourth order, and so on), as mentioned by Wetzels, Odekerken-Schröder, and Oppen (2009). The main reasons for using hierarchical component models can be summarized in three. First, for theoretical reasons (Wetzels et al., 2009), that is, when the construct can be operationalized by different conceptual dimensions of the same conceptual domain defined and supported in the literature. In this regard, it is added that the theory provides a research option on how to operationalize a concept, whether at one or more levels of abstraction. Thus, the construct can be operationalized (either in a unidimensional or multidimensional way) by seeking a theoretically specified measurement for the study's research question.

Second, hierarchical component models can be used if this option can be supported by theory, for practical reasons, or theoretical parsimony of the model, that is, fewer relationships in the structural model (Becker et al., 2012).

Third, hierarchical component models are applicable as long as the theory supports this decision for statistical reasons to overcome collinearity problems between manifest variables of the same construct (Hair Jr. et al., 2018). However, hierarchical models, as warned by Sarstedt et al. (2019), should not be used to resolve issues of discriminant validity in the structural model, as lower order components must exhibit validity discriminant between themselves (in addition to the other constructs in the model, excluding its higher-order component), differently from what was suggested by Hair Jr. et al. (2017), of establishing hierarchical component models in the face of collinearity between constructs to resolve discriminant validity problems.

In the study carried out by Ringle et al. (2012), based on articles published in Management Information Systems Quarterly between 1992 and 2011, the four types of relationships between the most common components in PLS-SEM applications were revealed: reflective-formative (52%), formative-formative (24%), reflective-reflective (20%) and formative-reflective (4%). See Figure 1.

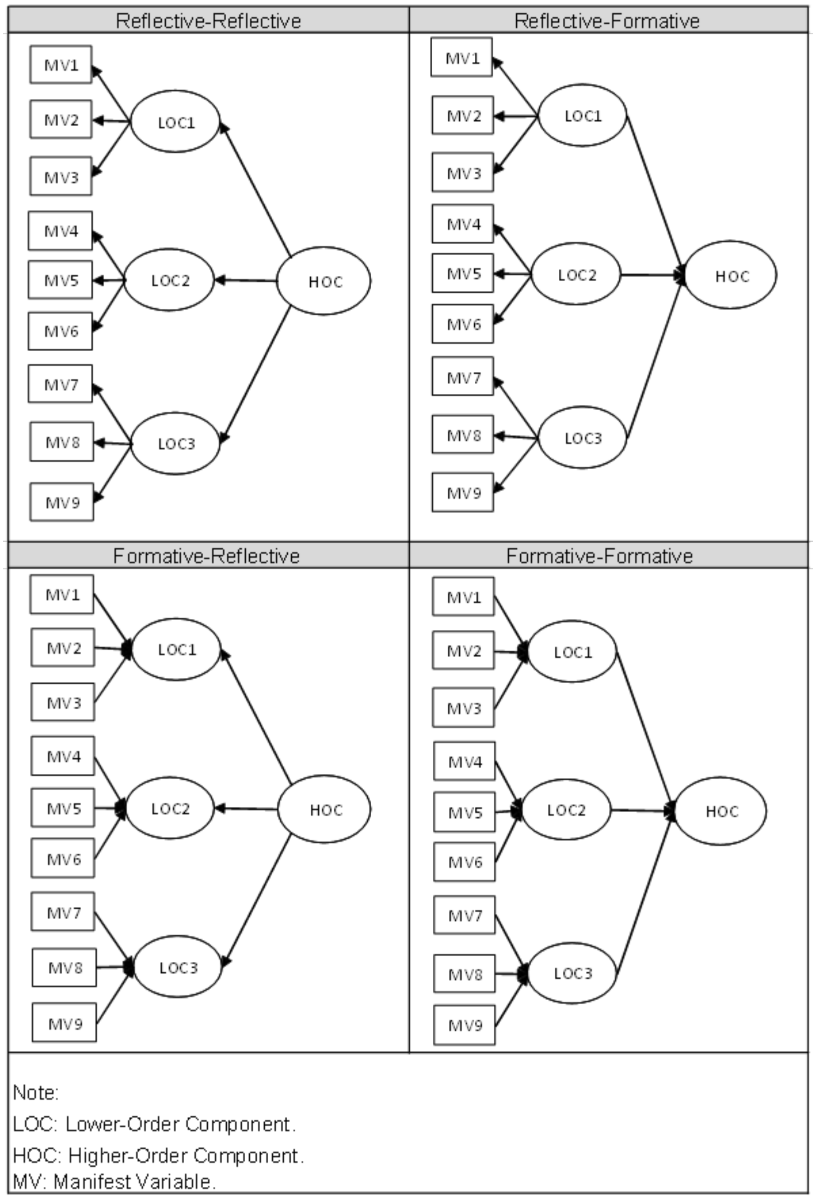


**Figure 1.** Types of second-order constructs.

Source: Adapted from Sarstedt et al. (2019, p. 198).

The relationship between the higher-order component (second-order) and the lower-order component (first-order) represents the nature of the higher-order latent variable. If the relationship is reflexive, the more abstract general concept (i.e., higher-order component) is represented (i.e., reflected) by its specific dimensions (i.e., lower-order components); on the other hand, if the relationship is formative, the general concept is constituted (i.e., formed) by the combination of its specific dimensions.

To model hierarchical constructs, then, one must define (i) how the lower-order components will be specified and the relationship between the higher-order component and its lower-order components, in addition to the approach used to estimate the higher-order component; (ii) which mode will be used to estimate the higher order component of the hierarchical measurement model, as well as the weighting scheme; and (iii) how to evaluate the higher and lower order components of the hierarchical model. This is discussed in sections 3, 4 and 5, respectively.

## 3 HOW TO SPECIFY HIERARCHICAL COMPONENT MODELS

In hierarchical component models, it is necessary, initially, to specify the measurement model for the lower-order components and the relationship between the higher-order component and its lower-order components, both relationships being able to be reflective or formative in nature (Sarstedt et al., 2019).

Next, it is essential to define the approach that will be used to estimate the higher-order component. Two widespread approaches stand out: the repeated measures approach (Lohmöller, 1989) and the two-stage approach.

As Sarstedt et al. (2019) explained, two procedures have been adopted for the two-stage approach: embedded two-stage approach (e.g., Wilson, 2010; Ringle et al., 2012), in which the higher-order component is used in the first stage; and the disjoint two-stage approach (Becker et al., 2012), which does not involve in the first stage the higher-order component in the path model.

Thus, in hierarchical component models, in addition to the specification of the lower-order components and the relationship between the higher-order component and the lower-order components, there is also the specification of the higher-order component itself when using the repeated measures approach or the embedded two-stage approach (first stage). Figure 2 shows an example of a formative-formative model with a higher-order component formatively specified.

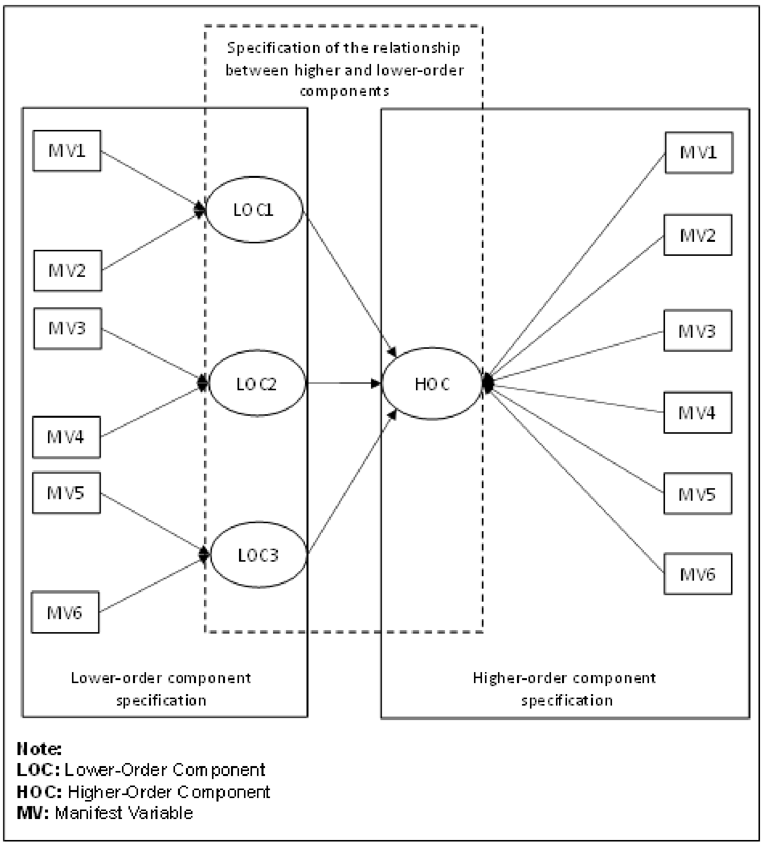


**Figure 2.** Types of specification of second-order constructs: repeated measures approach and embedded two-stage approach (first stage).

In the repeated measures approach, all manifest variables of the lower order component are assigned to the higher order component (Lohmöller, 1989). That is, manifest variables are used twice in second-order models. For example, in Figure 1, a hierarchical model of a higher-order component (HOC) with three lower-order components (LOC1, LOC2, LOC3) was presented, each measured by three manifest variables (MV1 to MV3, MV4 to MV6, and MV7 to MV9). In this case, the higher-order component would be specified with the same nine manifest variables as all lower-order components. See Figure 3 – A an example of a formative-formative construct.

For reflective-formative and endogenous formative-formative models, as an alternative to the repeated measures approach, the embedded two-stage approach (e.g., Ringle et al., 2012) and the disjoint two-stage approach (e.g., Becker et al., 2012) have been proposed. 2012). It is worth clarifying that although they have been proposed to overcome problems related to this type of construct, the two-stage approach (embedded and disjoint) can also be applied to formative-reflective and reflective-reflective models (Cheah et al., 2019).

In the embedded two-stage approach, in the first stage, the repeated indicators approach is used to estimate the scores of the latent variables of the lower-order components, which, in the second stage, serve as manifest variables of the higher-order component. Furthermore, all other constructs in the model are measured as single items by the latent variable scores for each construct obtained in the first stage (Ringle et al., 2012).

For example, the higher order component in Figure 1 (formative-formative model) would be measured in Stage 2 by the scores of the three latent variables of the lower order component obtained in Stage 1 by the repeated measures approach (see Figure 3 - B).

In the disjoint two-stage approach, the latent variable scores of the lower-order components are estimated in the first stage without the higher-order component in the path model. In the second stage, the scores obtained in the previous stage serve as manifest variables in the measurement model of the higher-order component (Becker et al., 2012). It also differs from the embedded version in how the other constructs in the model are measured, which are estimated using their composite measures.

For example, the higher order component in Figure 1 (formative-formative model) would be measured in Stage 2 by the scores of the three latent variables of the lower order component – obtained in Stage 1 without the presence of the higher order component (see Figure 3 - C). Figure 3 depicts the mentioned approaches.

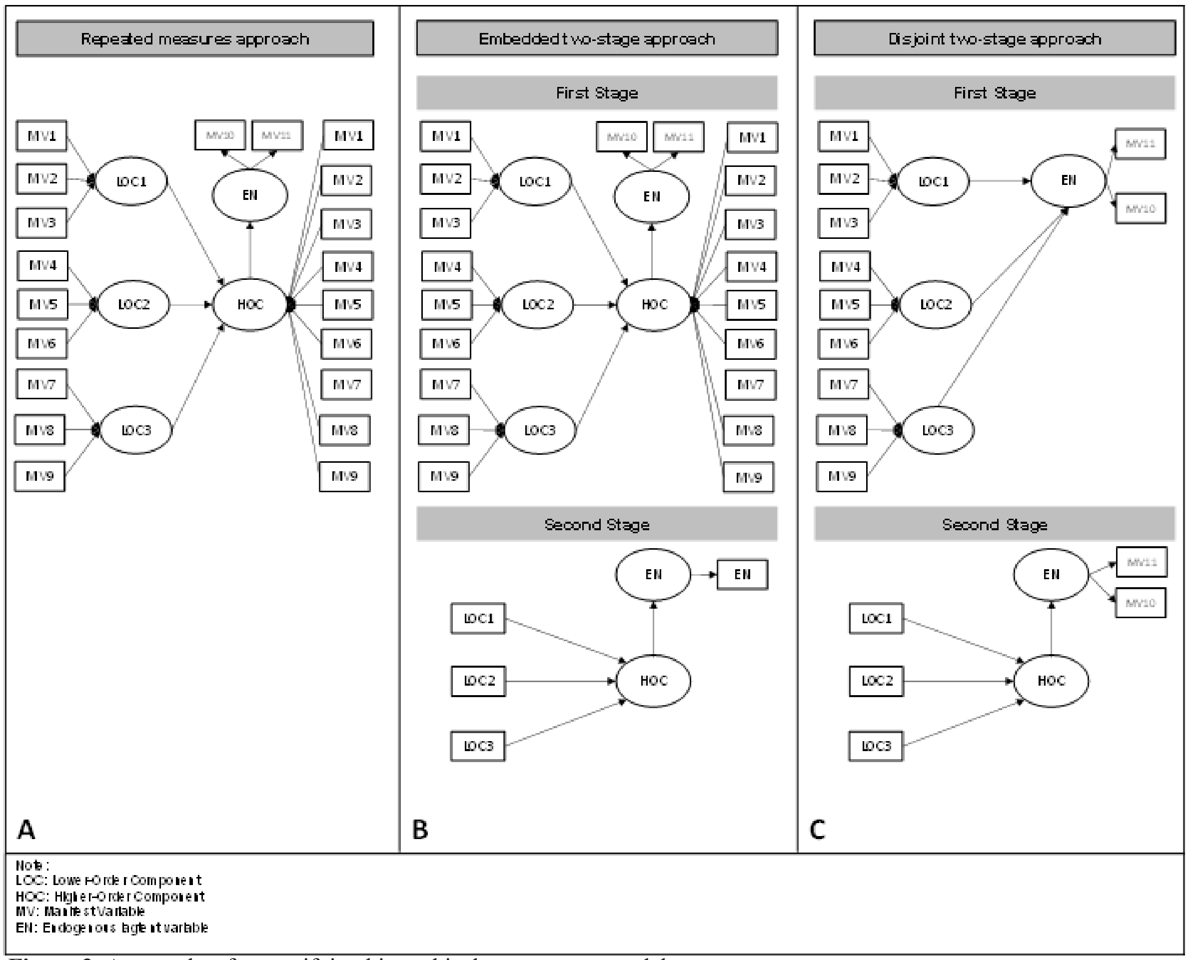


**Figure 3.** Approaches for specifying hierarchical components model.

A point that requires attention stands out in the embedded two-stage and repeated measures approaches. If the number of manifest variables is not similar between the lower order components, the relationships between the higher order component and the lower order components may become biased, precisely, due to the inequality in the number of manifest variables (Becker et al., 2012). Regarding this, Hair Jr. et al. (2018) suggest that the impact of excluding manifest variables (both in the lower and higher order components) be evaluated when the number of manifest variables in the lower order components is not similar.

In addition to this recommendation, it is warned that excluding manifest variables, especially in training models, can change the conceptual domain of the construct. For this reason, the disjoint two-stage approach is recommended when the number of manifest variables among lower-order components is different.

Sarstedt et al. (2019) highlight that when the sample size is large enough, the repeated measures approach and the two-stage approach tend to generate similar results. However, the authors suggest using the repeated measures approach when the objective is to reduce biases in the measurement model of the second-order construct. In contrast, the two-stage approach is more suitable for reducing biases in the structural model relationships. In summary, in hierarchical component models, the nature of the relationship between the latent variable of the lower-order component and its manifest variables is initially specified, and the relationship between the higher-order component and its lower-order components. However, how should the higher-order component be estimated concerning its manifest variables, whether in the repeated measures approach or the first step of the embedded two-stage approach? We will provide this answer in the next section.

## 4 HOW TO ESTIMATE HIERARCHICAL COMPONENT MODELS

When estimating hierarchical component models in PLS-SEM, one must define how the higher and lower-order components will be measured. That is, in a reflective way (Mode A) or formatively (Mode B).

In the formative model, the manifest variables are considered the cause of the latent variable. That is, the manifest variables form the latent variable. In reflective models, the latent variable causes the manifest variables. The manifest variables reflect the latent variable (Sanchez, 2013). Thus, Mode A is used to estimate reflective measurement models and Mode B formative ones.

There needs to be consensus on how to measure higher-order components in the embedded two-stage approach and the repeated measures approach. Generally, when using the embedded two-stage approach, the measurement mode in the second stage corresponding to the relationship of the higher-order component with the lower-order components is used. In other words, Mode A is for reflective-reflective and formative-reflective models, and Mode B is for reflective-formative and formative-formative models (Becker et al., 2012). Typically, when employing the embedded two-stage approach, the measurement mode in the second stage aligns with the relationship between the higher-order component and lower-order components. In simpler terms, Mode A is used for reflective-reflective and formative-reflective models, while Mode B is applied for reflective-formative and formative-formative models (Becker et al., 2012). Nevertheless, the recommendations on how to measure the higher-order component in the first stage of the embedded two-stage approach and the repeated measures approach need to be on the same page.

Specifically concerning the embedded two-stage approach, Ringle et al. (2012) measure the higher-order component using the exact specification as the lower-order components.

Regarding the repeated measures approach, Becker et al. (2012) recommend measuring formatively (Mode B) higher-order constructs in reflective-formative models. Regarding this recommendation, Hair Jr. et al. (2018) recommend caution – without clarifying the reason for this suggestion.

Regarding the two approaches, Hair Jr. et al. (2017, 2022) and Hair Jr. et al. (2018) propose that the way of measuring lower-order components be replicated in the higher-order construction.

Finally, Sarstedt et al. (2019), based on the findings of Becker et al. (2012), suggest that in hierarchical component models, reflective specifications on lower-order components should be configured in Mode A; and in formatives, in Mode B. On the other hand, even using the repeated measures approach or in the first stage of the embedded two-stage approach, according to the same authors, the measurement of the higher-order component must be specified according to its relationship with the lower-order component. Mode A is for reflective higher-order components, and Mode B is for formative higher-order components. Check the summary in Table 1.

**Table 1.** Hierarchical construct type and component measurement mode – repeated measures approach and embedded two-stage approach

| Types of hierarchical component models | Measurement models | | | |
|---|---|---|---|---|
| | Hair Jr. et al. (2017, 2022) | | Sarstedt et al. (2019) | |
| | Lower-order | Higher-order | Lower-order | Higher-order |
| Reflective-Reflective | Mode A | Mode A | Mode A | Mode A |
| Formative-Reflective | Mode B | Mode B | Mode B | Mode A |
| Reflective-Formative | Mode A | Mode A | Mode A | Mode B |
| Formative-Formative | Mode B | Mode B | Mode B | Mode B |

Another important aspect concerns the technique to estimate the latent variable (i.e., the internal weights estimation stage), that is, the weighting scheme of the internal approximation step of the PLS-SEM algorithm. There are three most common possibilities: centroid, factorial, and path. Henseler, Sarstedt, and Sinkovics (2009) present details of these three weighting schemes.

Hair Jr., Sarstedt, Ringle, and Mena (2012) and Hair Jr. et al. (2017, 2022) recommend that the centroid method not be used for hierarchical models.

On a different aspect, Becker et al. (2012) propose utilizing the path weighting scheme, the repeated measures approach, and the formative specification of higher-order constructs (i.e., Mode B) for hierarchical component models of the reflective-formative type. They discern that this arrangement, involving the repeated measures approach, a higher-order component specified by Mode B, and the path weighting scheme, results in improved parameter estimates.

Hair Jr. et al. (2018), in turn, recommend using the factorial scheme as a default in hierarchical component models and using the path method when a reflective higher-order construct is estimated formatively (Mode B) – following guidance from Becker et al. (2012).

Sarstedt et al. (2019), in turn, recommend, extrapolating the findings of Becker et al. (2012), that the path weighting scheme be used as a default configuration when estimating constructions of higher order in PLS-SEM.

Considering the four types of second-order models, the three approaches (repeated measures, two-stage embedded, and two-stage disjoint) and the two ways of specifying the higher-order component (modes A and B), in addition to the three weighting schemes (centroid, factor, and path), we reach 72 different possible configurations. From the discussion, a synoptic table is presented with the suggested configuration for each type of hierarchical component model (Table 2).

**Table 2.** Configuration for hierarchical component models

<table>
<tr><th colspan="2">Hierarchical component models</th><th rowspan="2">Approach</th><th rowspan="2">Weighting scheme</th><th rowspan="2">Higher-order component measurement mode</th><th rowspan="2">Source</th></tr>
<tr><th>Lower-order component</th><th>Higher-order component</th></tr>
<tr><td rowspan="2">Reflective</td><td>Reflective</td><td>Repeated measures</td><td>Path</td><td>A (reflexively)</td><td>Sarstedt et al. (2019)</td></tr>
<tr><td>Formative</td><td>Repeated measures</td><td>Path</td><td>B (formatively)</td><td>Becker et al. (2012)</td></tr>
<tr><td rowspan="2">Formative</td><td>Reflective</td><td>Repeated measures</td><td>Path</td><td>A (reflexively)</td><td>Extrapolando os achados de Becker et al. (2012)</td></tr>
<tr><td>Formative</td><td>Repeated measures</td><td>Path</td><td>B (formatively)</td><td>Hair Jr. et al. (2018) e Sarstedt et al. (2019)</td></tr>
</table>

It is explained that the recommendation to measure the higher-order component in the same way as the relationship between this component and the lower-order component, in the same vein as Sarstedt et al. (2019), arises from empirical evidence provided by Becker et al. (2012) about reflective-formative models; and the logic that supports the nomological network of the model.

While Becker et al. (2012) findings pertain specifically to reflective-formative models, the same principle applies by extension – acknowledging the necessity for additional investigation.

In addition to Table 2, the recommendation to use the disjoint two-stage approach is reinforced when the number of variables manifested between lower-order components is different.

Having defined how the hierarchical component models will be specified and estimated, it is crucial to know how they should be evaluated – especially the higher-order component.

## 5 HOW TO VALIDATE HIERARCHICAL COMPONENT MODELS

Having defined how the hierarchical component models will be specified and estimated, it is crucial to know how they should be evaluated – especially the higher-order component.

When evaluating hierarchical component models in PLS-SEM, three steps are taken: (1) measurement of lower-order components, which follows the same criteria for evaluating unidimensional (i.e., non-hierarchical) construct models; (2) measurement of higher-order components, for which the latent variables of the lower-order components play the role of manifest variables; and, in the case of the repeated measures approach, (3) assessment of the explanatory power of the hierarchical construct (i.e., the relationship between the higher-order component and its lower-order components).

Thus, the higher-order component should not be evaluated in terms of its manifest variables (i.e., the manifest variables repeated by the repeated measures approach or the first step of the embedded two-stage approach), nor the relationships between the lower and higher-order components should be evaluated as part of the structural model. Only the higher-order component makes up the structural model (Sarstedt et al., 2019). Check the summary in Appendix A.

Four general observations are worth:

First, according to the understanding of Hair Jr. et al. (2018), in reflective-reflective and formative-reflective models, the lower-order components reflect the higher-order component. Hence, the direction of the relationships is from the higher-order component to the lower-order component. Therefore, they represent loads (outer loading) despite being mapped as path coefficients in PLS-SEM. On the other hand, in reflective-formative and formative-formative models, the lower-order components form the higher-order component. Accordingly, the direction of the relationships is from the lower-order component to the higher-order component. Consequently, even though they express path coefficients in PLS-SEM, they represent outer weights equally. Thus, the same evaluation criteria as the measurement model for unidimensional constructs are applied to the relationships between higher and lower-order components.

Second, in assessing discriminant validity, the lower-order components must exhibit discriminant validity among themselves and all other constructs in the model, except for the higher-order component of which they are a part. Likewise, the higher-order component must exhibit discriminant validity for all other constructs in the model (Sarstedt et al., 2019).

Third, in reflective-reflective and formative-reflective models, the coefficients of determination ($R^2$) of the lower-order components can be interpreted as how much of the higher-order component is reflected in the lower-order components (Wetzels et al., 2009). Likewise, the average of the redundancy index indicates how much of the variation in the manifest variables of the lower-order components explains the variation in the manifest variables of the higher-order component (Sanchez, 2013).

Fourth, using the repeated measures approach, in reflective-reflective and formative-reflective type models, the loadings of the relationships between the higher-order component and the lower-order components are used to determine the internal consistency reliability, convergent validity and discriminant validity.

In turn, to analyze the quality of adjustment of the structural model, it is necessary to consider only the higher-order construct, evaluating the collinearity between the constructs, the significance and relevance of the path coefficients, and the coefficient of determination ($R^2$) (Sarstedt et al., 2019). Collinearity must present values less than 5 (Hair et al., 2017). $R^2$, in turn, can be considered strong, moderate, or weak for values of 0.75, 0.5, and 0.25, respectively (Hair, Ringle & Sarstedt, 2011). Regarding the significance and relevance of path coefficients, Becker et al. (2022) recommend a bootstrapping of at least 10,000 samples. The authors suggest using enough observations to achieve high power and a conservative threshold for statistical significance. PLS-SEM can be implemented in various software, such as SmartPLS, ADANCO, and StatisME, or through packages for R software, such as semPLS, plspm, and SEMinR, among other alternatives.

It is unknown whether this form of assessment has been implemented for reflective-reflective and formative-reflective models. Therefore, it should be carried out in a way that is complementary to these tools' standard outputs.

On the other hand, using the two-stage approach (embedded or disjoint), the score of the latent variables of the lower-order components is used to measure the higher-order latent variable so that it is not necessary to perform the calculation in a complementary way, being able to use the results presented in the outputs of those software/packages.

In addition, Appendix B presents a comparative table of the indicators in SmartPLS and in the R plspm package, which were identified as the most used in the survey carried out in this study.

## 6 SUMMARY AND CONCLUSIONS

The PLS-SEM technique allows the analysis of complex interrelationships of various organizational and behavioral aspects (Hair Jr. et al., 2018). It has been used in different areas, such as people management (e.g., Cavalcanti, Felix & Mainardes, 2022), accounting (e.g., Pazetto & Beuren, 2022), entrepreneurship (e.g., Campos et al., 2021), etc.

Particularly in the area of Accounting, studies on behavior could be addressed using PLS-SEM as a data analysis approach. For example, the effect of leadership styles and turnover intention; the impact of the intention to use technology on the relationship between the adoption of information systems on the organization's financial and non-financial performance; the relationship of ESG (Environmental, Social and Governance) dimensions to the organizational climate, among other possibilities.

This article presented guidelines for reporting the configuration used in second-order hierarchical component models and their evaluation, summarized in Figure 4.

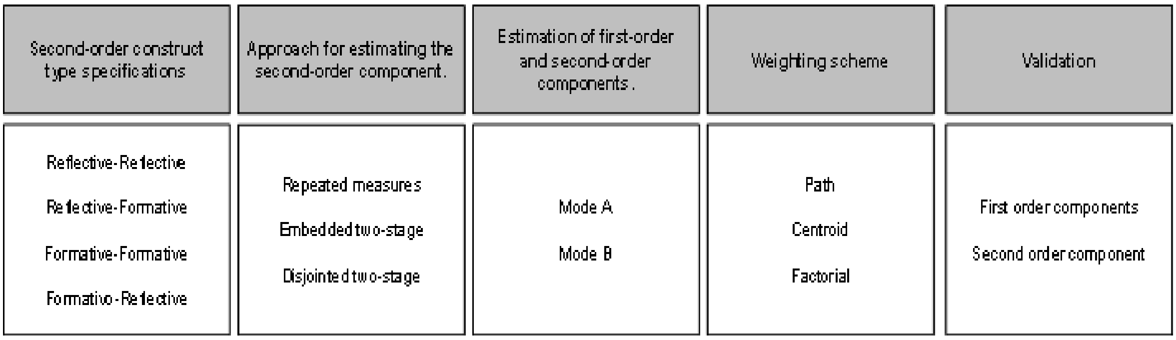


**Figure 4.** Synthetic summary of decision steps – Second-order constructs using PLS-SEM.

Regarding the configuration (see Table 2 and Figure 4), researchers must first report the type of hierarchical component model (e.g., formative-reflective). This is important to guide the choice of model configuration.

Second, they must explain the approach used to estimate the model (e.g., repeated measures).

Third, they need to report the mode of specification of the higher-order component (mode A or B) in the repeated measures approach and in the first step of the embedded two-stage approach, for which it is suggested that the nature of the higher-order component (i.e., its relationship with lower order components) is adopted as a measurement mode.

Fourth, they must inform the weighting scheme of the internal approximation step of the PLS-SEM algorithm (e.g., path).

This way, the reader will have clarity about the procedures adopted, favoring the transparency of the research and the reproduction of the results.

Fifth, using the repeated measures approach, in reflective-reflective and formative-reflective models, the loadings of the relationships between the higher-order component and the lower-order components should be used to determine the reliability measures of internal consistency, convergent validity and discriminant validity. Evaluating the results related to using manifest variables from the lower-order components repeated in the higher-order component is inappropriate. If the program used to process the PLS-SEM technique does not have the results of these measurements in this way, it is necessary to carry out the calculations in parallel.

Adjustments to the measurement model are made through an iterative process, with the re-estimation of the model after removing variables, one by one, evaluating the impact on internal consistency, convergent validity and discriminant validity in order to achieve a better fit of the model, it does not rule out that researchers may feel discouraged from using the repeated measures approach, thus opting for the two-stage approach (embedded or disjoint).

Regarding the evaluation of the hierarchical component model, initially, it is necessary to evaluate the adequacy of the lower order components according to guidelines for their measurement method (reflective or formative); then, the adequacy of the higher order component must be assessed, according to the standard for evaluating the form of its relationship with the lower-order components (reflective or formative). When the number of manifest variables among lower-order components differs, the disjoint two-stage approach is suggested.

Although this study contributes to understanding the use of second-order hierarchical component models in PLS-SEM, the study focuses on less complex models that do not involve mediation and moderation relationships, for example, which is an essential limitation of the study. Furthermore, future research could be aimed at understanding hierarchical component models that involve moderating and mediating unidimensional latent variables and also models in which the hierarchical component acts as a moderator or mediator in the structural model.

Finally, it is highlighted that part of the improvement of the methodological foundations of the PLS-SEM method related to hierarchical component models still needs to be carried out in parallel, explicitly using the repeated measures approach. Following the improvements and extensions of the method, software support and packages are expected to be developed.

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## APPENDIX A

**Table 1.** Evaluation of the measurement model for hierarchical constructs

| Dimension | Lower-order component | | Higher-order components [the lower-order components represent the manifest variables of the higher-order component] | |
|---|---|---|---|---|
| | Reflexive | Formative | Reflexive | Formative |
| Internal consistency reliability[a] | * 0.7 ≤ Cronbach's alpha ≤ 0.9<br>* 0.7 ≤ composite reliability ≤ 0.9<br>* 0.7 ≤ Consistent reliability coefficient ≤ 0.9<br>* First eigenvalue greater than 1 and second eigenvalue less than 1 or much smaller than the first eigenvalue. | - | * 0.7 ≤ Cronbach's alpha ≤ 0.9<br>* 0.7 ≤ composite reliability ≤ 0.9<br>* 0.7 ≤ Consistent reliability coefficient ≤ 0.9<br>* First eigenvalue greater than 1 and second eigenvalue less than 1 or much smaller than the first eigenvalue. | - |
| Convergent validity | * Outer loading ≥ 0.708<br>*Average Variance Extracted (AVE) ≥ 0.5 | Redundancy analysis: correlation between the formative construct and its alternative measurement (reflective or global single item) ≥ 0.708 | * Outer loading ≥ 0.708<br>*Average Variance Extracted (AVE) ≥ 0.5 | Redundancy analysis: correlation between the formative construct and its alternative measurement (reflective or global single item) ≥ 0.708 |
| Discriminant validity | * Cross-loadings (loadings of the manifest variables of a construct must be greater than all its cross-loadings with other constructs)<br>* Fornell-Larcker criterion: The square root of the construct's AVE must be higher than its correlation with the others.<br>* Heterotrait–Monotrait ratio of correlation (HTTM): for conceptually similar constructs, HTMT < 0.9 and for conceptually different constructs, HTMT < 0.85. The confidence interval of the HTMT statistic should not include the threshold value for all combinations of constructs. | - | * Cross-loads (loads from the relationships between the higher-order component and the lower-order components of the same hierarchical construct must be greater than all its cross-loads with other constructs)<br>* Fornell-Larcker criterion: The square root of the construct's AVE must be higher than its correlation with the others.<br>* Heterotrait–Monotrait ratio of correlation (HTMT): for conceptually similar constructs, HTMT < 0.9 and for conceptually different constructs, HTMT < 0.85. The confidence interval of the HTMT statistic should not include the threshold value for all combinations of constructs. | - |

**Table 1.** Evaluation of the measurement model for hierarchical constructs

| Dimension | Lower-order component | | Higher-order components [the lower-order components represent the manifest variables of the higher-order component] | |
|---|---|---|---|---|
| | Reflexive | Formative | Reflexive | Formative |
| Collinearity | - | * Variance Inflation Factor (VIF) < 5 (manifest variables) * Tolerance > 2 | - | * Variance Inflation Factor (VIF) < 5 (latent variables) * Tolerance > 2 |
| Significance and relevance of relationships | - | Outer weight[b] of significant manifest variables or loads (outer loading) ≥ 0.5 or significant loads (p-value < α) | - | Outer weight[b] of the relationships of the higher order component with the significant lower order components or loads (outer loading) ≥ 0.5 or significant loads (p-value < α) |
| Explanatory power | Lower-order component | | | |
| | Reflective-Formative and Formative-Formative | | Reflective- Reflective and Formative- Reflective | |
| | - | | *Coefficient of determination[c] ($R^2$) *Redundancy index average | |

Source: From Sanchez (2013), Hair Jr. et al. (2017, 2022), Hair Jr., Sarstedt, Ringle, and Gudergan (2018), Sarstedt et al. (2019), Hair Jr., Hult, Ringle, Sarstedt, Danks, and Ray (2021) and Sarstedt, Hair Jr., and Ringle (2022).

[a] Cronbach's alpha may constitute the lower boundary and composite reliability the upper boundary of internal consistency reliability. The consistent reliability coefficient generally lies between Cronbach's alpha and composite reliability; thus, it can be a good representation of the internal consistency reliability of the construct.

[b] Regarding the indicator's relevance, it should be considered that the maximum weight obtained for uncorrelated manifest variables is *1n*, with *n* being the number of manifest variables (Hair Jr. et al., 2017, p. 146).

[c] In PLS-SEM, the coefficient of determination indicates explanatory power (and not predictive), as Sarstedt, Hair Jr., and Ringle (2022) explained. Cohen (1988, p. 477-478) proposes the following gradation for $R^2$, from the gradation for effect size in multiple regression ($f^2$), visto que *f2=R21-R2*: 0.0196 (small), 0.13 (medium) and 0.26 (large).

**APPENDIX B**

**Table 2.** Comparison between SmartPLS and package plspm

| Criterion | | | SmartPLS (v. 3.3.9) | plspm (v. 0.4.9) |
|---|---|---|---|---|
| Internal consistency reliability (unidimensionality) | | Cronbach's alpha | X | X |
| | | Composite reliability (Jöreskog's rho) | X | |
| | | Consistent reliability coefficient (Henseler-Dijkstra's rho) | X | |
| | | Composite reliability (Dillon-Goldstein's rho) | | X |
| | | Eigenvalue | | X |
| Convergent validity | Reflective model | Average Variance Extracted (AVE) | X | X[a] |
| | | Outer loading | X | X |
| | | Commonality of item | | X |
| | Formative model | Redundancy Analysis[b] | X | |
| Discriminant validity | | Cross load | X | X |
| | | Fornell-Larcker criterion | X | |
| | | Heterotrait-Monotrait ratio (HTMT) | X | |
| Collinearity | | Variance Inflation Fator (VIF) | X | |
| | | Tolerance | X | |
| Significance and relevance of manifest variables | | Outer weight and outer loading | X | X |
| | | Significance (*p-value*) | X | X |
| | | Intervalo de confiança | X | X |
| | | Confidence interval | X | X |
| Explanatory power | | Coefficient of determination ($R^2$) | X | X |
| | | Average redundancy index | | X |

[a] The plspm package considers AVE (i.e., Construct Commonality) in evaluating the structural model.

[b] It should not be confused with the average redundancy index present in the plspm package since the redundancy analysis refers to the correlation between the formative construct and its alternative measurement (reflective or global single item), and the average redundancy index is equal to $R^2$ x AVE.