Journal of Marketing Analytics (2025) 13:709–724
https://doi.org/10.1057/s41270-025-00414-6

SOFTWARE REVIEW

Covariance-based structural equation modeling (CB-SEM): a SmartPLS 4 software tutorial

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Revised: 7 May 2025 / Accepted: 8 May 2025 / Published online: 7 June 2025

Abstract

Covariance-based structural equation modeling (CB-SEM) enables researchers to estimate models with hypothesized cause-effect relationships between latent variables (i.e., constructs), each of which is operationalized by several items (i.e., indicators). To conduct CB-SEM analyses, researchers can rely on a range of software applications. However, many of these applications require researchers to engage in sometimes complicated and error-prone programming tasks. While IBM SPSS AMOS provides a graphical user interface (GUI), it does not fully meet the expectations of contemporary software. In order to address these challenges, the statistical SmartPLS 4 software has recently introduced a new CB-SEM module, which improves the user experience through a modern and intuitive graphical interface and comprehensive result reports. This tutorial describes the key CB-SEM analysis steps (i.e., model setup, estimation, and results evaluation) using the SmartPLS software.

Keywords CB-SEM · CFA · Confirmatory factor analysis · Covariance-based structural equation modeling · SEM · SmartPLS

Introduction

Structural equation modeling (SEM) is a general multivariate analysis framework that allows researchers to empirically test theoretically established models with relationships between constructs, typically operationalized by multiple indicators (Sarstedt et al. 2016). To estimate structural equation models, researchers can draw on various estimators, which differ in terms of how they statistically approximate constructs and model relationships (Cho et al. 2022). Arguably the most prominent and widely developed estimator is covariance-based SEM (CB-SEM) via maximum likelihood estimation (MLE; Jöreskog 1978, 1993). Numerous articles provide introductions to CB-SEM, document its widespread impact on the management and marketing literature, and offer guidance on best practices (e.g., Bagozzi and Yi 1988; Rigdon 1998; Iacobucci 2010; Diamantopoulos and Riefler 2011; Hair et al. 2017; Baumgartner and Weijters 2020; Zyphur et al. 2023). Additionally, several textbooks offer a comprehensive understanding of how to use CB-SEM in research and practice (e.g., Diamantopoulos and Siguaw 2000; Raykov and Marcoulides 2006; Byrne 2016; Whittaker and Schumacker 2022; Kline 2023).

While the origins of SEM go back to the early twentieth century, it was only with the advent of late twentieth century computing power and the development of multiple commercial software applications, such as EQS, LISREL, and Mplus, that SEM procedures became prominent among academic researchers. These software applications relied predominantly on manual specification of the model in some

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form of coded syntax. Today, the lavaan package of the R statistical software (R Core Team 2022) offers a free and open-source alternative that is widely applied by researchers to perform CB-SEM analyses, but still requiring users to specify the model using syntax. An approach to avoid coding the model in a syntax emerged with the introduction of *AMOS: Analysis of Moment Structures* (Arbuckle 1989). A few years after AMOS's introduction as a standalone option that relied predominantly on a graphical user interface (GUI), IBM acquired the SPSS software and it became a widely used SEM application. Academics and practitioners appreciated the ease of using the AMOS point-and-click interface to build their models and to visualize the results (Hair et al. 2014).

IBM SPSS AMOS was developed more than 30 years ago, however, and has changed very little in terms of the GUI. The software's user interface and overall usability therefore do not fully align with current standards. As an alternative, the statistical SmartPLS software (https://www.smartpls.com; Ringle et al. 2024), which has been developed for SEM analyses using partial least squares (Wold 1982; Lohmöller 1989; Chin 1998), now includes a CB-SEM module with a modern GUI—among other methods such as multiple regression analysis, logistic regression, necessary condition analysis, path analysis, and generalized structured component analysis (GSCA; Hwang and Takane 2004). Prior reviews of the SmartPLS software emphasize the software's intuitive design and ease of use (e.g., Sarstedt and Cheah 2019). Several textbooks (e.g., Hair et al. 2022, 2024; Chua 2024), articles (Matthews et al. 2016; Sarstedt et al. 2024b; Merkle 2025), and software reviews (e.g., Memon et al. 2021; Cheah et al. 2024; Sarstedt et al. 2024b) have highlighted the potentials of the SmartPLS software and provided guidance on its use for a wide range of statistical analyses. However, the application of the SmartPLS software in a CB-SEM context has not yet been documented.

In light of the above, this tutorial article demonstrates how to conduct a CB-SEM analysis using the SmartPLS 4 software. To do so, we draw on the case study used in Hair et al. (2019; i.e., Chaps. 9 to 12), which ranks among the most widely used textbook on multivariate data analysis in the social sciences (e.g., Black and Babin 2019). Our illustrations aim at helping researchers to reliably run CB-SEM analyses, thereby facilitating the use of the full spectrum of SEM estimators in order to safeguard the results' robustness when using methods with different assumptions (e.g., Sarstedt et al. 2024a).

In the following, we first describe the case study and principles of CB-SEM estimation, followed by a step-by-step description of model setup, estimation, and results evaluation using SmartPLS 4. This software tutorial article concludes with additional observations and SmartPLS software extensions that can be expected in the near future.

Case study and model estimation

Our illustrations draw on the employee retention model (Fig. 1) and the data ($N=400$) used in Hair et al. (2019). The model has two main elements (Anderson and Gerbing 1988): Structural and measurement models.

The structural model defines the dependence (single-headed arrows) and correlation (double-headed arrows) among constructs of interest (larger circles in Fig. 1). Researchers typically distinguish between endogenous and exogenous constructs. Endogenous constructs are dependent in that they are being explained by other constructs in the model; unexplained variance is captured by error terms, represented by the small circles in Fig. 1. Exogenous constructs only explain other constructs in the model and are thus independent.

The employee retention model's objective is to understand and explain the effects that organizational commitment (*OC*) and job satisfaction (*JS*) have on employees' staying intentions (*SI*). In addition, the model considers the work environment perceptions (*EP*) of employees and their attitudes toward their co-workers (*AC*) as antecedents of *OC* and *JS* (Fig. 1). The directed paths demonstrate the hypothesized relationships in the model and the double-headed arrows depict the correlations between exogenous (i.e., independent) constructs. Hair et al. (2019) allow the covariance between *AC* and *EP* to be freely estimated (i.e., unconstrained), as indicated by the double-headed arrow between these constructs, since the two constructs are both related to the environment in which they work. Leaving this arrow out would constrain the covariance between the two constructs to zero, which may result in substantial differences in the model fit and could also influence (change) other parameter estimates for the relationships between the constructs.

The measurement models specify how indicators or items (rectangles in Fig. 1) represent the constructs of interest. More specifically, the indicators are seen as manifestations or reflections whose variance the underlying construct explains. Analogous to the structural model, the small circles in Fig. 1 represent the indicators' error terms, capturing their unexplained variance.[1] A construct is usually operationalized by several indicators aimed at ensuring the reliability and validity of the constructs meets established guidelines. Measurement theory specifies which items are associated with a particular construct and the estimates either confirm or reject the measurement theory. Research articles, especially those focusing on scale development (e.g., Relling et al. 2016; Becker et al. 2024) and scale handbooks (e.g., for marketing; Bearden et al. 2011; Bruner 2021) provide researchers with information on how to operationalize

[1] Note that the measurement models can also consider potential correlations between error terms.

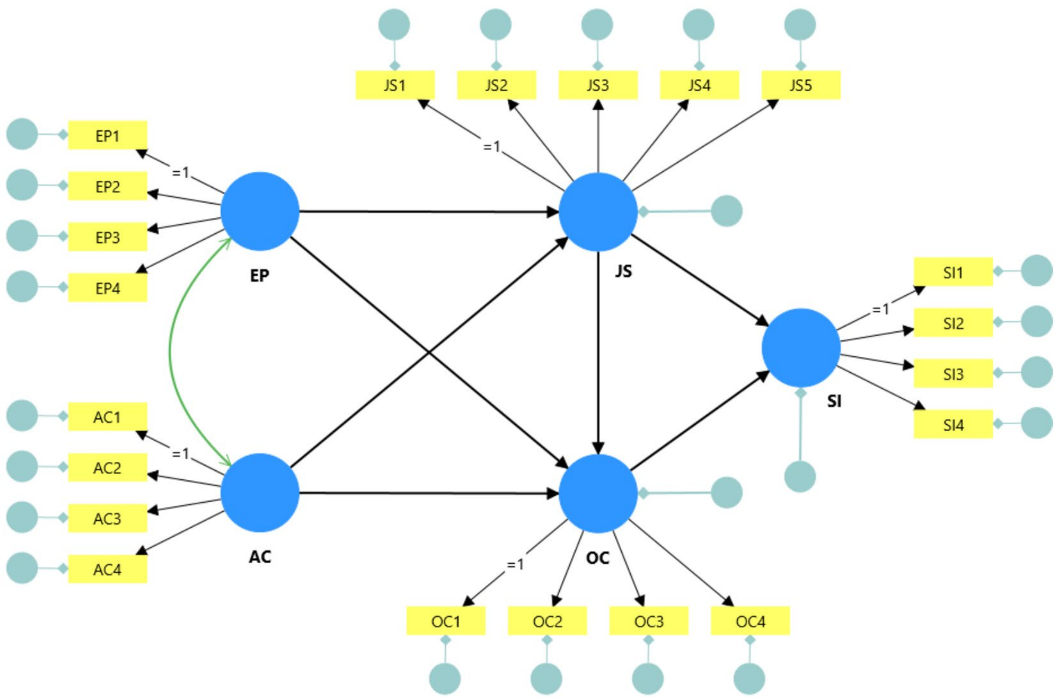

Fig. 1 Employee retention model (Hair et al. 2019, Chap. 11)

constructs. Each of the constructs in the employee retention model is operationalized with between four and five indicators. Table 10.2 in, Chapter 10 Hair et al. (2019) shows the scales used for the indicators and the survey questions.

To estimate a model such as in Fig. 1, CB-SEM combines aspects of both confirmatory factor analysis (CFA) and multiple regression analysis. By constructing a series of equations depicting both the direct relationships between constructs and their indirect effects (i.e., through another construct in the structural model), SEM can simultaneously analyze multiple dependent relationships, enabling researchers to establish complex theoretical models that assume a network of interdependencies among constructs. More specifically, CB-SEM simultaneously estimates parameters for all equations involved in a model by trying to reproduce the observed covariance matrix and, at the same time, meet the requirements of the theoretically imposed constraints. In a model with no theoretically imposed constraints, the procedure would perfectly reproduce the observed covariance matrix. Such a model would be referred to as saturated because it has no degrees of freedom and is generally not of theoretical interest. MLE is the most widely applied method for calculating CB-SEM results. While other options are available, including generalized least squares, weighted least squares, and a variety of distribution-free estimators (e.g., Boomsma and Hoogland 2001), MLE provides a relatively robust estimation approach (Iacobucci 2009; Hair et al. 2017).

The goal of MLE is to determine the parameters of the specified model (given some constraints) to obtain the best model fit. The model fit represents how well the data (more specifically, the observed covariance matrix S) matches the a-priori theoretical structure (more specifically, the model-implied covariance matrix Σ). The results can guide researchers in testing whether the hypothesized theoretical model with its estimated relationships reflects the observed data structure. In addition, researchers apply several additional criteria to evaluate and ensure the quality of the results obtained for the estimated model.

Case study illustration using the SmartPLS 4 software

Hair et al. (2019, Chapter 10) suggest that a comprehensive CB-SEM analysis comprises of six stages:

- Stage 1—Defining individual constructs.
- Stage 2—Developing the overall measurement model.
- Stage 3—Designing a study to produce empirical results.
- Stage 4—Assessing the measurement model (CFA).
- Stage 5—Specifying the structural model.
- Stage 6—Assessing the structural model (CB-SEM).

Stages 1 through 4 focus on the construct operationalization on the grounds of measurement theory and their validation using CFAs as highlighted by Anderson and Gerbing (1988); see also Baumgartner and Weijters (2020) and Hair et al. (2019, Chapter 10).

Stages 5 and 6 focus on the test of latent construct structure; that is, the directional relationships between the constructs as implied by structural theory. In practically all cases, this analysis is more constrained than the first because the typical assumption when configuring a CFA is that all constructs are related to all other constructs. Thus, the structural theory assessment in Stages 5 and 6 is formed by specifying directional relationships between relevant theoretical constructs, and by adding constraints to the CFA to indicate where relationships between factors should not exist.[2]

After creating Hair et al.'s (2019, Chap. 11) model using SmartPLS, and estimating it by means of CB-SEM, we specifically focus on Stages 4 and 6, which deal with the assessment procedures for the measurement and structural models. The measurement model assessment essentially applies the criteria used in a CFA, which Hair et al. (2019), for example, explain in their Chapter 10. In Stage 6, assessing the structural model, researchers are primarily interested in the model fit. If the measurement model demonstrates adequate fit and other indicators of construct reliability and validity, then researchers proceed with the interpretation of the structural model.

Model and data

The SmartPLS 4 software has the employee retention model included as a sample project file. The project includes the model, as described above, and the original data from Hair et al. (2019). The data are synthetic, representing employee responses as collected by an established marketing research company. Specifically, the data comprise $N=400$ responses from HBAT Industries (HBAT), an international paper product manufacturer, and meet all the assumptions of CB-SEM, including normally distributed data and to some extent homoskedasticity.

To import the project, open the **Workspace view** and go to **Sample projects**. Navigate to the **CB-SEM/CFA** sample projects and tick the boxes next to **Covariance-based SEM (CB-SEM)** and **Confirmatory factor analysis (CFA)** (Fig. 2).

Next, the **Example—Confirmatory factor analysis (CFA)** and **Example—Covariance-based SEM (CB-SEM)** appear in the SmartPLS **Workspace**. The sample projects include several models and datasets. For illustrative purposes, we delete all the models except the **Hair et al. MDA textbook** model in the **Example—Confirmatory factor analysis (CFA)** and **Example—Covariance-based SEM (CB-SEM)** projects. When we right-click on this selection, a dialog with several options opens. Select the **Delete resource** option and confirm the deletion in the subsequent dialog box. Similarly, we delete all datasets except the **Hair et al. (HBAT) [400]**. Each **Example—Confirmatory factor analysis (CFA)** and **Example—Covariance-based SEM (CB-SEM)** project in the **Workspace** now only contain one model and one dataset, as shown in Fig. 3.

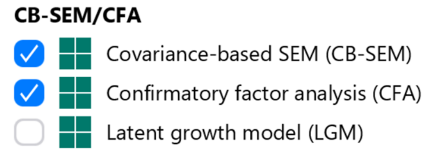

Fig. 2 Importing sample projects into the SmartPLS software

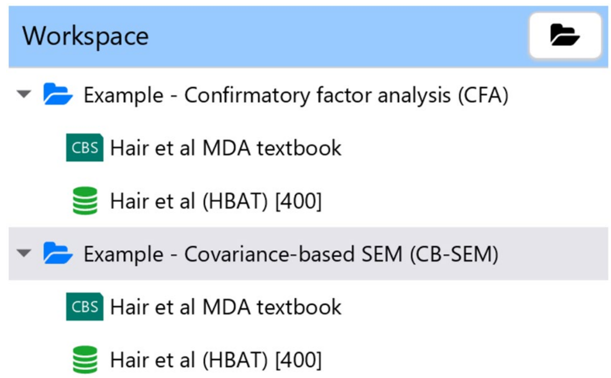

Fig. 3 Projects in the SmartPLS software

Double-clicking on **Hair et al. (HBAT) [400]** opens the **Data View**, which shows the indicators and their descriptive statistics, such as the minimum and maximum values, the mean values, skewness, kurtosis, etc. In addition, there is an option to examine the correlation matrix. Next, to start with a CFA, double-click on the **Hair et al. MDA textbook** model in the **Example—Confirmatory factor analysis (CFA)** project in order to open the **Modeling View**, which displays the CFA model as shown in Fig. 4. The model shows the constructs and their indicators. One loading estimate per measurement model is constrained to 1 (i.e., the first indicator per construct in this example). Such a procedure allows us to identify the scale of the construct. You can set and change constraints by double-clicking on a relationship, which opens a dialog for this purpose. Constraints can also be set on constructs (or error terms) to constrain the parameter, which would be an alternative to identify the scale of a construct. The model also displays the indicators' error terms. If reasonable, you can also add covariances/correlations between the error terms by using the **Correlation** option in the menu bar. They are represented

[2] This would be the case for recursive models. In the rare instance of a nonrecursive model, the CFA may be more constrained.

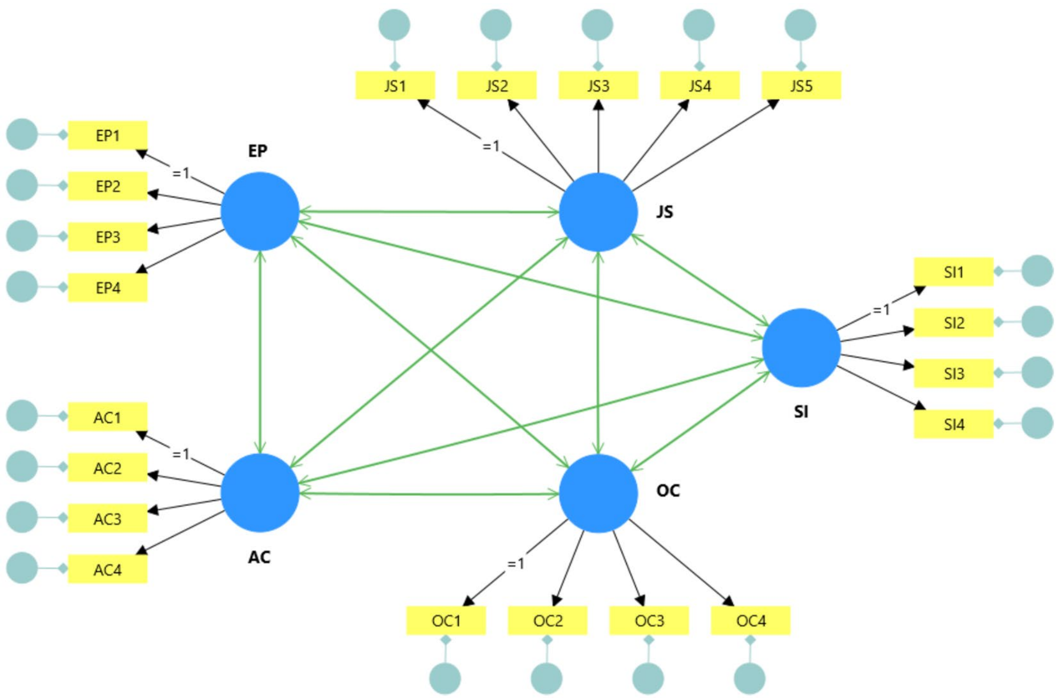

Fig. 4 CFA of the employee retention model constructs (Hair et al. 2019, Chap. 10)

by double-headed arrows between the constructs.[3] It is also possible to constrain these correlations.[4] Next, we follow the steps in the SmartPLS software to obtain this model's CFA results.

CFA model estimation

Before the model estimation, you need to safeguard unidimensionalty (Hair et al. 2019, Chap. 10). Unidimensional measures mean that a set of measured variables (indicators) can be explained by only one underlying construct. Unidimensionality becomes critically important when more than two constructs are involved. In such a situation, each indicator is hypothesized to relate to only a single construct. All cross-loadings and error variance and covariance are hypothesized to be zero when unidimensional constructs exist.

Moreover, you need to ensure the model is identified as explained by Hair et al. (2019, Chap. 10). Model identification ensures that enough information exists to compute a solution for a set of structural equations using CB-SEM. In contrast, an identification problem (an unidentified model) leads to an inability of the proposed model to generate estimates as finding a solution is mathematically impossible. The three possible conditions of identification are overidentified, just-identified, and underidentified. The model used in this example is identified as demonstrated in detail by Hair et al. (2019, Chap. 10). The SmartPLS software uses a simple test to evaluate if the model is underidentified and issues a warning.

To estimate the model by using the maximum likelihood CB-SEM algorithm, click on the **Calculate** button in the menu bar and select **Basic CB-SEM algorithm**. The SmartPLS software opens a dialog box (Fig. 5), which enables the user to specify several algorithm settings, such as the maximum number of iterations and the stop criterion (Table 1).

We recommend researchers should keep the default settings. Next, in the **Basic CB-SEM algorithm** start dialog box, ensure that the box next to **Open report** has been ticked and click on the **Start calculation** button. The SmartPLS software will then estimate the CFA model, and the **Results View** will open.

The **Results View** initially shows the model and selected parameter estimates on the right-hand side (Fig. 6), while different result report elements appear on the left-hand side.

[3] If you want, you can also display the correlation between the constructs in a curved manner. To do this, left-click on a connection and select it. Then a point appears in the middle of the connection, which you can click on with the left mouse button and move to change the straight lines into curved ones.

[4] By default, if no correlation is drawn between error terms or exogenous constructs the correlation is constrained to zero. Drawing a correlation allows freely estimating the correlation until it is constrained to a specific value by the user by double-clicking on the correlation and setting a fixed value. Correlations (as well as all other parameters) can also be constrained to be equal by using the same string (e.g., "a") for all correlations that should be equal.

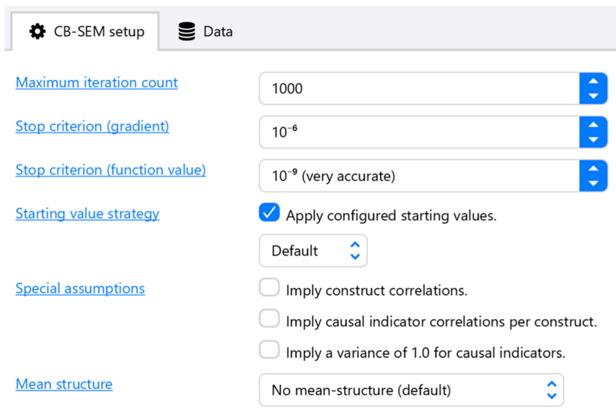

Fig. 5 Basic CB-SEM algorithm start dialog box

The box labeled **Graphical output** on the lower left side enables you to choose different types of parameter estimates to be shown in the displayed model. For example, when selecting **Path coefficients (standardized)** under **Structural model**, and **Weights/loadings (standardized)** under **Measurement model**, the standardized coefficients' results are shown on the model's graphical output.

Moving to the results report, we can, for example, select **Factor loadings—Matrix (standardized)** under **Final results**. When clicking on this menu item, the **Results View** appears on the right-hand side, showing the **Factor loadings—Matrix (standardized)** results. In this new output, factor loadings above 0.70 appear in green, while loadings below 0.70 are red—as we will discuss in the measurement model assessment stage. Finally, we can save the results report in the menu bar of the SmartPLS software (i.e., the results report appears under the project in the **Workspace View**), or in **Excel** format, and in **HTML** files for use outside of the software.

Measurement model assessment

Following the systematic procedure for measuring model assessment as outlined by Hair et al. (2019, Chaps. 9 and 10), we carry out the following analyses to evaluate the model fit as well as the reliability and validity of the constructs:

- Overall fit.
- Reliability and factor loadings.

Table 1 CB-SEM algorithms settings in SmartPLS

Setting	Explanation
Maximum iterations	The maximum number of iterations the optimizer will perform. This parameter should be high enough to ensure a good model solution. The default value is 1,000, but could be higher in more complex models
Starting value strategy	*Apply configured starting values*. By checking this option, the user can specify its own starting values for the free model parameters. If this option is not selected, the software will use the default starting values
	Default strategy. This strategy mimics Lavaan's default starting values. It uses Fabin-style estimates for its loadings, 0.0 for path coefficients and covariances, a 0.5*indicator variance for its error variances, and 0.05 for factor error variances
	One zero strategy. This strategy applies more simple starting values, 1.0 for loadings and variances, and 0.0 for path coefficients and covariances
Stop criterion (gradient)	The optimizer stops when one of the two stop criteria is fulfilled, and convergence to the optimum is assumed. In this case, the optimizer terminates when ‖g‖ < stop criterion * max(1, ‖x‖), where ‖.‖ denotes the Euclidean (L2) norm. The default value is 10^-6
Stop criterion (function value)	The optimizer stops when one of the two stop criteria is fulfilled and convergence to the optimum is assumed. In this case, the optimizer terminates when the decrease in the objective function (maximum likelihood value) is smaller than the recommended minimum. The condition is met if (f′–f)/f < stop criterion, where f′ is the objective value of the previous iteration and f is the objective value of the current iteration. The default value is 10^− 9
Special assumptions	*Imply latent variable correlations*. Select this option if you want to freely estimate the correlations between all the exogenous constructs. Usually, if no correlation arrow is drawn in the model, the correlation between the exogenous constructs is constrained to zero. With this option, the correlations are also estimated freely when no arrow is drawn
	Imply causal indicator correlations per construct. Select this option if you want to estimate the correlations between all the causal indicators of a construct. Usually, if no correlation arrow is drawn in the model, the correlation between the causal indicators is constrained to zero. With this option, the correlations are also estimated freely when no arrow is drawn
	Imply a variance of 1.0 for causal indicators. If we choose this option, all the variances of causal indicators are constrained to 1.0. This also overwrites use-specified values. This option should help mimic the default Lavaan results

Source: SmartPLS webpage, https://www.smartpls.com/documentation/algorithms-and-techniques/cbsem/, Accessed May 2025

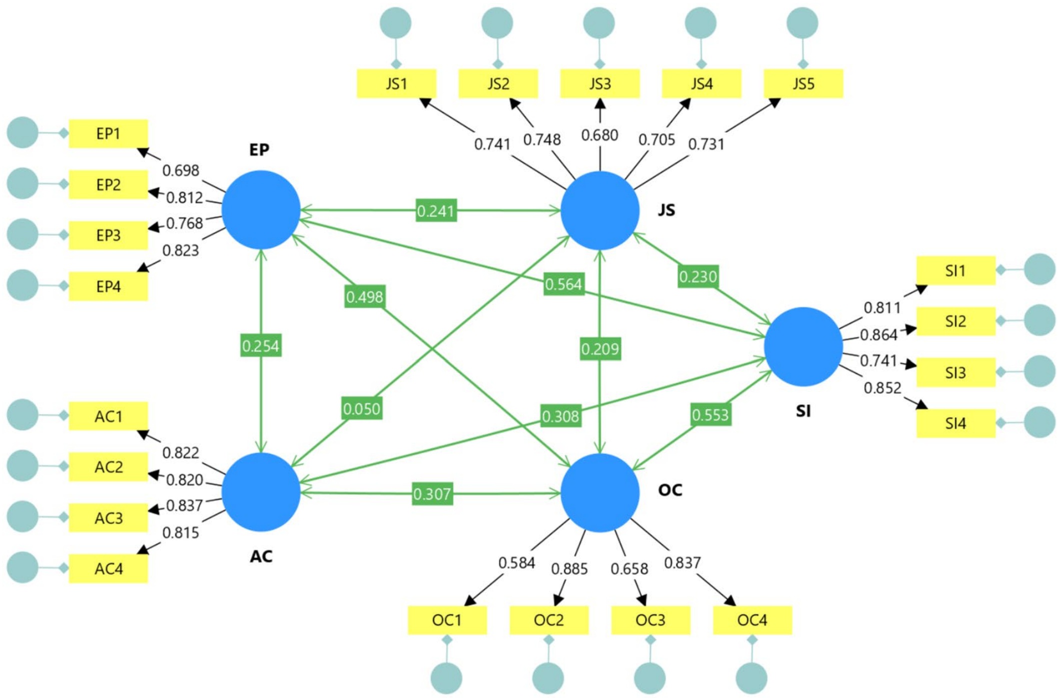

Fig. 6 Graphical output (displaying factor correlations and standardized loadings)

- Validity (i.e., convergent validity, nomological validity, discriminant validity).[5]

The above metrics are interpreted to confirm the measurement models. When these metrics meet established guidelines, as recommended by Hair et al. (2019), the measurement models can be confirmed.

The assessment of the model's fit builds on a comparison of the observed indicator covariance matrix (S) and the model-implied covariance matrix (Σ) by means of a χ^2 test. The smaller the difference between the two covariance matrices, the better the model fit. In "close-fitting" models, the χ^2 would not differ significantly from 0. However, statistical power and model complexity serve to make that possibility rare in large models with large samples. Both conceptually and practically, the model fit is the most critical result for testing a theoretical model in CB-SEM. Research has proposed a series of different metrics that quantify the degree of model fit. Hair et al. (2019, Chap. 9) describe these metrics in greater detail and offer suggestions for cutoff values (i.e., their Table 9.4), depending on (1) the sample size (N), and (2) the number of observed variables in the model (m). These metrics include:

- The χ^2 value and the associated degrees of freedom (df).
- Absolute fit indices, such as the goodness-of-fit index (GFI), the root mean square error of approximation (RMSEA), or the standardized root mean residual (SRMR).
- Incremental fit indices, such as the comparative fit index (CFI) or the Tucker-Lewis index (TLI).
- Badness-of-fit indices (e.g., RMSEA, SRMR).
- The adjusted theoretical fit index (ATFI) offers a useful scrutiny of the theoretical structural and measurement models' relative fit.

No single "magic" fit index value separates poor-fitting and well-fitting models. Further, applying a single set of cut-off rules to all measurement models, and for that matter, to all models of any type, is not reasonable. The quality of the fit depends strongly on the model characteristics, including the sample size and the model complexity. Therefore, multiple fit indices should be used to assess a model's goodness-of-fit. Researchers may also apply flexible cutoff values which consider the specific data (sample size) and model parameters (Niemand and Mai 2018; McNeish and Wolf 2023).

To obtain the model fit results, return to the SmartPLS **Workspace** and double-click on the **Hair et al. MDA**

[5] Note: In addition, you need to ensure face validity, which is the extent to which the content of the items is consistent with the construct definition. Face validity is based solely on the researcher's judgment and was established based on the content of the corresponding items (Hair et al. 2019, Chap. 10).

	Estimated model	Null model
Chi-square	237.489	4452.358
Number of model parameters	52.000	21.000
Number of observations	400.000	n/a
Degrees of freedom	179.000	210.000
P value	0.002	0.000
ChiSqr/df	1.327	21.202
RMSEA	0.029	0.225
RMSEA LOW 90% CI	0.018	0.219
RMSEA HIGH 90% CI	0.038	0.231
GFI	0.948	n/a
AGFI	0.933	n/a
PGFI	0.735	n/a
SRMR	0.035	n/a
NFI	0.947	n/a
TLI	0.984	n/a
CFI	0.986	n/a
AIC	341.489	n/a
BIC	549.045	n/a

Fig. 7 Model fit results of the confirmatory factor analysis (CFA)

textbook model in the **Example—Confirmatory factor analysis (CFA)** project. The **Modeling View** opens, which enables you to click on the **Calculate** button. Select the **Basic CB-SEM algorithm** option for obtaining results of the CFA model, **Start calculation**, and **Open results**. In the results report, under **Quality criteria**, the SmartPLS software displays the **Model fit** outcomes as shown in Fig. 7. Note that the null model is hypothesized to be the simplest model that can be theoretically justified. It serves as the baseline or comparison standard used in incremental fit indices (i.e., that's why other indices show n/a as result for the null model in Fig. 7). We focus on the estimated model's results, which represent the outcomes of the theoretically established and specified model shown in Fig. 6.

For the overall fit assessment (i.e., to test the discrepancy between the sample and the model-implied covariance matrices), researchers often revert to the χ^2 value, which represents a badness of fit measure in the sense that generally, a higher value is associated with relatively worse fit (depending on df). For a close fit, the statistical null hypothesis that the observed and model-implied covariance matrices do not differ would be supported. In that case, the χ^2 value would *not* be statistically significant and, thus, *not* indicate that the difference between observed and model-implied covariance matrix is different from zero (e.g., Kline 2023; Chap. 10). However, the χ^2 test typically displays statistical significance (i.e., indicating a poor-fitting model)—as in our example (Fig. 7).

Because of this inherent limitation of the χ^2-test, researchers typically report other fit statistics, most of which are mathematical variations of the χ^2 value, null model χ^2 value, df and sample size. The normed χ^2, which is the χ^2 value relative to the degree of freedom (df), give an alternative picture: Researchers consider that ChiSqr/df value of 3 (in some cases, even up to 5) or less represents a good model fit (Dash and Paul 2021). In our example, the ChiSqr/df value is 1.327 (Fig. 7), which support the model fit. However, reporting the normed χ^2 value without the actual χ^2 value and df is inappropriate because while it is easy to know the normed value from actual (and df), the reverse is not true. For additional model fit assessment criteria, Hair et al. (2019, Chap. 9) provide critical cut-off values. For the results shown in Fig. 7, we find that the root mean square error of approximation (RMSEA) has a value of 0.029, with a 90 percent confidence interval of 0.018 to 0.038. Although 0 is not in the confidence interval, the RMSEA value is relatively low. The comparative fit index (CFI) and Tucker-Lewis index (TLI) outcomes of 0.986 and 0.984 are above 0.94. The standardized root mean square residual (SRMR) has a value of 0.035, which is below 0.08. Based on these outcomes, we conclude that the model has relatively good fit.

Next, we focus on the indicator reliability metric. This metric is evaluated by examining the standardized indicator loadings. Hair et al. (2019, Chaps. 9 and 10) provide detailed explanations and rules of thumb. To view the standardized loadings results in the SmartPLS software, click on **Final results → Outer loadings → Matrix (standardized)**. The results in Fig. 8 show most of the indicators' standardized loadings are above the assumed minimum value of 0.70. Four indicators have loadings between 0.50 and 0.70, which is below the recommended guideline. While these standardized loadings are lower than desired, they do contribute in a meaningful way and are therefore acceptable in principle. Thus, in line with Hair et al. (2019, Chap. 10), we retain these indicators in the model to support content validity for these constructs.[6]

High indicator reliability usually results in high internal consistency reliability for the construct, which is assessed based on the coefficient alpha (i.e., Cronbach's α). This criterion remains widely used, even though researchers acknowledge that this metric probably underestimates reliability. High values in these metrics indicate that the items consistently reflect the same underlying construct. Researchers usually expect that Cronbach's α to be above 0.7 (Hair

[6] Note that loadings with a standardized value of 0.50 or higher are usually statistically significant. Consequently, we do not examine the individual items' statistical significance at this stage of the measurement model assessment. However, interested researchers could check whether the loadings are significant as a component of the significance testing of the overall structural model relationships. This analysis is available in List (unstandardized) and shows all indicator loadings are significant.

	AC	EP	JS	OC	SI
AC1	0.822				
AC2	0.820				
AC3	0.837				
AC4	0.815				
EP1		0.698			
EP2		0.812			
EP3		0.768			
EP4		0.823			
JS1			0.741		
JS2			0.748		
JS3			0.680		
JS4			0.705		
JS5			0.731		
OC1				0.584	
OC2				0.885	
OC3				0.658	
OC4				0.837	
SI1					0.811
SI2					0.864
SI3					0.741
SI4					0.852

Fig. 8 Results table of standardized factor loadings

et al. 2019, Chap. 10). In SmartPLS' **Construct reliability and validity** results report (Fig. 9), this outcome appears in the **Cronbach's alpha (standardized)** column. All the construct reliability values are above 0.80 in our example, providing support for the measures' internal consistency reliability.

To establish convergent validity, we examine the average variance extracted (AVE). The AVE metric indicates how much variance a construct explains in its associated indicators (Hair et al. 2019, Chap. 10). The AVE is calculated as the average of all of the squared standardized factor loadings, divided by the number of indicators in the corresponding measurement model. An AVE of 0.50 or higher is generally considered an acceptable threshold since it indicates the construct explains at least one-half of its associated indicators' variance. Conversely, an AVE below 0.50 indicates that, on average, more than half of the variance remains unexplained in the items associated with the underlying construct on which they load. It is essential to compute an AVE for each latent construct separately. We can access the AVE results by clicking on **Quality criteria → Construct reliability and validity**. The results in Fig. 9 show that all AVE values are larger than 0.50, thereby supporting convergent validity.

Discriminant validity measures the extent to which a construct or variable is empirically distinguishable from others in the model. Robust discriminant validity therefore indicates a construct is relatively unique and captures aspects other measures do not explain. To measure discriminant validity, we recommend using the HTMT criterion, which contrasts the correlations of indicators measuring different constructs with the correlations of indicators measuring the same construct (Henseler et al. 2015; Voorhees et al. 2016). Researchers evaluate the HTMT values for each pair of constructs with lower values indicating support for discriminant validity (Franke and Sarstedt 2019; Ringle et al. 2023). Henseler et al. (2015) recommend a threshold value of 0.90 if the constructs are conceptually similar. But when two constructs are conceptually distinct, a lower threshold of 0.85 is acceptable. Researchers may also test whether an HTMT value is significantly lower than a specific threshold using bootstrapping (Efron and Tibshirani 1993; Davison and Hinkley 1997).[7]

To obtain the discriminant validity results, click on **Calculate** and select the **CB-SEM bootstrapping** option. As shown in Fig. 10, a dialog box for the bootstrapping setting appears. To assess the HTMT results, you need to change the default settings. First, under the **Amount of results** category, you need to select the **Complete (slower)** option. Selecting this option ensures the bootstrapping results reported in the SmartPLS software also include the HTMT values' outcomes. Second, under **Test type**, you should select **One-tailed** (while keeping the **Significance level** at **0.05**) (Franke and Sarstedt 2019; Ringle et al. 2023). If the

	Cronbach's alpha (standardized)	Cronbach's alpha (unstandardized)	Composite reliability (rho_c)	Average variance extracted (AVE)
AC	0.894	0.891	0.893	0.679
EP	0.857	0.848	0.851	0.603
JS	0.844	0.281	0.639	0.520
OC	0.832	0.823	0.827	0.564
SI	0.889	0.886	0.887	0.670

Fig. 9 Construct reliability and validity results

[7] Note that you can only execute the bootstrapping analysis in CB-SEM if you use raw data.

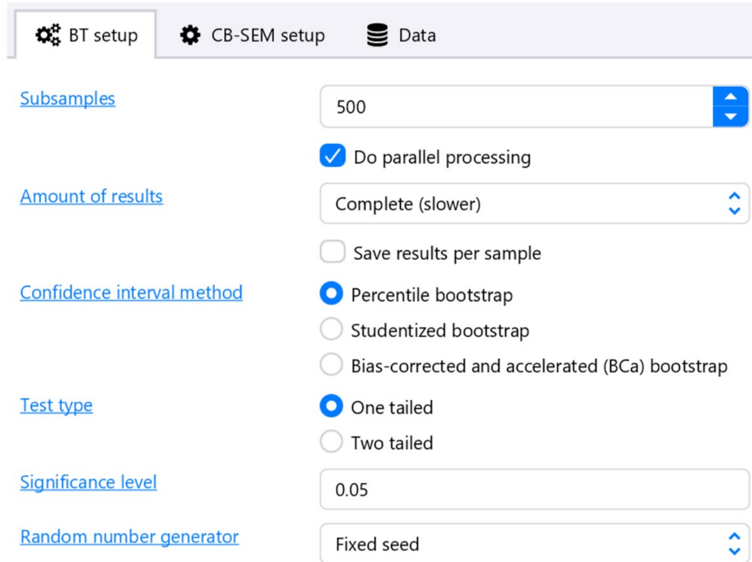

Fig. 10 CB-SEM bootstrapping settings to assess HTMT results

Fig. 11 HTMT results and bootstrapping confidence intervals

	Original sample (O)	Sample mean (M)	5.0%	95.0%
EP -> AC	0.257	0.257	0.164	0.347
JS -> AC	0.066	0.095	0.057	0.156
JS -> EP	0.244	0.246	0.166	0.324
OC -> AC	0.275	0.279	0.198	0.360
OC -> EP	0.495	0.498	0.407	0.591
OC -> JS	0.209	0.211	0.128	0.301
SI -> AC	0.310	0.311	0.225	0.389
SI -> EP	0.569	0.570	0.480	0.652
SI -> JS	0.232	0.232	0.154	0.312
SI -> OC	0.501	0.504	0.414	0.592

resulting 95th percentile is below the critical HTMT value of 0.85 (or 0.90), you can conclude that the corresponding HTMT value is significantly lower than this cutoff value (with a 5% probability of error), thereby establishing discriminant validity.

After adjusting the settings in the start dialog box of the **CB-SEM bootstrapping** routine, click on the **Start calculation** button. The SmartPLS software's **Results View** opens after completion of the computations. Under **Quality criteria → Heterotrait-monotrait ratio (HTMT) → Confidence intervals**, you find the results as shown in Fig. 11.[8] All the upper boundaries of the confidence intervals (**95.0%** in Fig. 11) are below the more conservative cutoff value of 0.85, providing support for the discriminant validity of the construct measures.

To summarize, the measurement model assessment results empirically support our theoretically derived constructs specifying how the indicators correspond to latent constructs. In addition to the measurement model assessment presented in this section, researchers may also consider local fit measures (Baumgartner and Weijters 2020). This kind of assessment is particularly useful when researchers face challenges in ensuring model fit, as it helps identify the source of the problem.

Structural model assessment

Next, we evaluate the structural model. To do so, we conduct the following steps: we re-evaluate the model fit assessment (now for the full structural model), the significance of the

[8] Note: As an alternative, you can access the bias-corrected confidence interval to account for systematic difference between average sample estimates and the population value by clicking the corresponding tab. The results differences are usually marginal in empirical applications and, as such, do not lead to different decisions, except for borderline cases which should be anyway interpreted carefully.

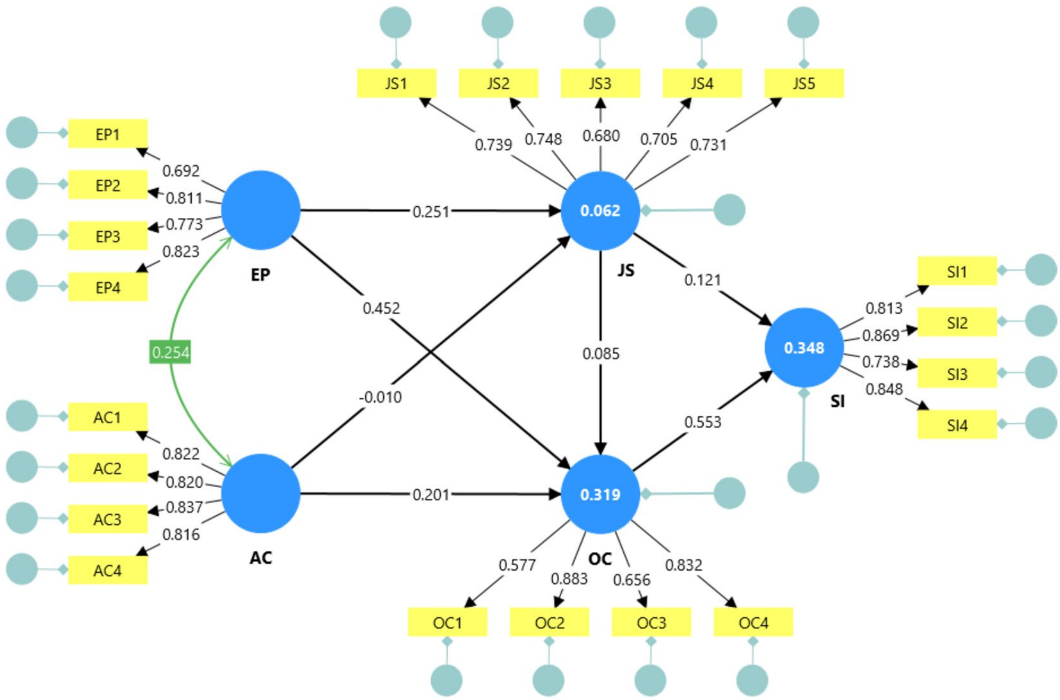

Fig. 12 Graphical representation of the full structural model including results

structural model's coefficients, and the structural model relationships' relevance, which focuses on the size of the path coefficient and if they are sufficiently large enough to justify a meaningful interpretation (Fig. 12).

To assess the full theoretical model, including the structural model, the emphasis is again first on the overall model fit, which is a key CB-SEM evaluation criterion. We do so by evaluating whether the theoretically established model's estimated relationships are consistent with the real-world observations (see our previous explanations on model fit). The information in Fig. 13 displays the overall fit statistics from testing the HBAT employee retention model, which are similar to the model fit results of the CFA model (Fig. 7). In line with our prior model fit results discussion, we find that that the CB-SEM results support the overall model fit (see Hair et al. 2019, Chap. 9, for a review of fit guidelines).

The model validation is not complete without examining the individual parameter estimates. The questions to pose include: Are the model parameters statistically significant? And are they practically meaningful?

In the SmartPLS software's **Results View**, we can examine the structural model's unstandardized and standardized path coefficients via the **Final results → Path coefficients → List (unstandardized)** and **→ List (standardized)**. As shown in Fig. 14, most standardized path coefficients are large enough to support a meaningful interpretation of the relationships (i.e., above 0.20).

However, the relationships from *AC* to *JS* (– 0.010), *JS* to *OC* (0.085), and *JS* to *SI* (0.121) are weak. It is therefore essential to determine if these relationships are statistically significant.

We first answer this question by looking at the **Final results → Path coefficients → List (unstandardized)** (Fig. 15). The standard errors displayed here are derived analytically from the MLE and are often referred to as normal-theory standard errors. The results show that the relationships from *AC* to *JS* and *JS* to *OC* are not significant, while the relationship between *JS* to *SI* is significant on a 5% level, but not on a 1% level.

We can also again answer this question by running the **Bootstrapping** routine with the default settings to get nonparametric standard errors and confidence intervals. This is especially helpful when assessing the significance of indirect and total effects for which the normal theoretic standard errors do not apply (Preacher and Hayes 2008). Another advantage of the bootstrapping results is that we can also get standard errors and confidence intervals for the standardized path coefficients.

If you are still in the SmartPLS software's **Results View**, click on the **Edit** button in the menu bar to return to the modeling window. Now click on **Calculate** and select **Bootstrapping**. The dialog with the default setting options is shown in Fig. 16.[9] If you changed the settings in previous analyses, click on the **Default settings** button on the lower left side of the dialog box. Make sure the check box next to

[9] Note that the default bootstrapping settings displayed in Fig. 16 differ from those shown in Fig. 10. You can restore the default settings by clicking on **Default settings** in the bootstrapping start dialog.

Fig. 13 The HBAT goodness-of-fit statistics

	Estimated model	Null model
Chi-square	284.529	4452.358
Number of model parameters	50.000	21.000
Number of observations	400.000	n/a
Degrees of freedom	181.000	210.000
P value	0.000	0.000
ChiSqr/df	1.572	21.202
RMSEA	0.038	0.225
RMSEA LOW 90% CI	0.029	0.219
RMSEA HIGH 90% CI	0.046	0.231
GFI	0.938	n/a
AGFI	0.921	n/a
PGFI	0.735	n/a
SRMR	0.060	n/a
NFI	0.936	n/a
TLI	0.972	n/a
CFI	0.976	n/a
AIC	384.529	n/a
BIC	584.102	n/a

	Path coefficients (standardized)
AC -> JS	-0.010
AC -> OC	0.201
EP -> JS	0.251
EP -> OC	0.452
JS -> OC	0.085
JS -> SI	0.121
OC -> SI	0.553

Fig. 14 The structural model's standardized path coefficients

Open report is checked, and click on the **Start calculation** button. This enables the results' computation to start. The results report will open automatically when the calculations are completed.

In the bootstrapping results report, you now need to click on **Final results → Path coefficients (standardized) → Confidence intervals** to display the results in Fig. 17. To support statistical significance, zero should not fall into the 95% bootstrap confidence interval. All but two structural path estimates are significant and in the expected theoretical direction. The exceptions are again the estimates of the paths from *AC* to *JS* and from *JS* to *OC*. Hence, we cannot empirically support these two theoretically hypothesized relationships. However, given that

Fig. 15 The structural model's unstandardized path coefficients, standard errors, and *p*-values

	Parameter estimates	Standard errors	T values	P values
AC -> JS	-0.009	0.051	0.169	0.866
AC -> OC	0.256	0.068	3.761	0.000
EP -> JS	0.196	0.048	4.045	0.000
EP -> OC	0.519	0.078	6.631	0.000
JS -> OC	0.126	0.078	1.603	0.110
JS -> SI	0.087	0.037	2.355	0.019
OC -> SI	0.269	0.033	8.147	0.000

Fig. 16 The CB-SEM bootstrapping start dialog box in SmartPLS

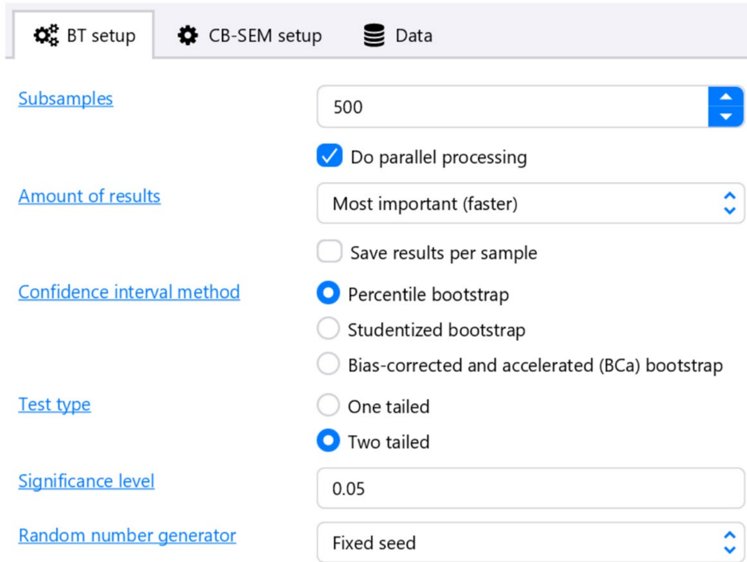

Fig. 17 Bootstrapping results of the standardized path coefficients

	Original sample (O)	Sample mean (M)	2.5%	97.5%
AC -> JS	-0.010	-0.008	-0.121	0.107
AC -> OC	0.201	0.204	0.102	0.297
EP -> JS	0.251	0.251	0.150	0.354
EP -> OC	0.452	0.451	0.319	0.578
JS -> OC	0.085	0.085	-0.020	0.184
JS -> SI	0.121	0.120	0.031	0.213
OC -> SI	0.553	0.553	0.440	0.656

five of the seven estimates are consistent with individual hypotheses, these results support the theoretical model, with a caveat regarding the two non-significant paths.

In CB-SEM, researchers often focus solely on the coefficients' statistical significance. This approach is, however, superficial, because relationships with relatively low standardized coefficients (e.g., 0.085 in our example) could become statistically significant if the dataset has a large number of observations (the HBAT data's sample size is $N = 400$). In other words, the relevance of the relationships should also be evaluated when inspecting the results. For example, both of the *SI* coefficients are statistically significant. However, with a standardized path coefficient of 0.533, the *OC* construct is much more relevant for explaining *SI* than *JS,* which has a direct effect of only 0.121.

In line with these results, one could argue that *OC* mediates the relationship between *JS* and *SI*. However, when multiplying these coefficients, we find that this indirect effect has a value of only 0.047. In the SmartPLS software's bootstrapping **Results View**, we can choose **Final results → Indirect effects → List (standardized)** to display the outcomes shown in Fig. 18. We find that the indirect effect from *JS* via *OC* to *SI* is not statistically significant suggesting that *OC* does not represent mediator of the relationship between *JS* and *SI*. Consequently, the total effect (i.e., the direct effect plus the indirect effect) of *JS* to *SI* does not substantially improve compared to the direct effect. As a result, *JS* remains considerably less relevant than *OC* in explaining *SI*.

To summarize, the overall results for the metrics support the model's fit. More specifically, five of the model's seven relationships were also supported with meaningful and significant path estimates (Fig. 15).

Observations and conclusion

Based on the CB-SEM analytical framework and a case study by Hair et al. (2019), this article offers a comprehensive introduction how to conduct a CB-SEM analysis using the SmartPLS software. We demonstrate how a model is set up, estimated, and evaluated in SmartPLS—starting with the measurement model assessment using a CFA, followed

Fig. 18 Bootstrapping results of the standardized specific indirect

	Original sample (O)	Sample mean (M)	2.5%	97.5%
AC -> JS -> OC	-0.001	-0.001	-0.013	0.011
AC -> OC -> SI	0.111	0.113	0.051	0.177
AC -> JS -> SI	-0.001	-0.001	-0.017	0.015
EP -> JS -> OC	0.021	0.021	-0.006	0.051
EP -> OC -> SI	0.250	0.251	0.160	0.346
EP -> JS -> SI	0.030	0.031	0.004	0.065
JS -> OC -> SI	0.047	0.047	-0.012	0.099
AC -> JS -> OC -> SI	-0.000	-0.001	-0.007	0.006
EP -> JS -> OC -> SI	0.012	0.012	-0.003	0.027

by the structural model assessment on the grounds of CB-SEM results. As such, this article provides comprehensive guidelines for scholars wanting to carry out their CB-SEM analyses with the SmartPLS software.

Extending our fundamental CFA and CB-SEM analysis demonstrations using SmartPLS, researchers could also access and utilize additional analyses such as mediator, moderator (i.e., by adding an interaction term), moderated mediation, and conditional process analyses (e.g., Hayes 2022) for which the SmartPLS software directly delivers the CB-SEM results without the need to employ PROCESS (Sarstedt et al. 2020). Another possible option is to compare the model estimates from alternative structural equation modeling techniques such as generalized structured component analysis (GSCA; see, for example, Hwang and Takane 2014) and partial least squares structural equation modeling (PLS-SEM; see, for example, Hair et al. 2022). Researchers using the SmartPLS software can easily convert a model generated for CB-SEM into a PLS-SEM or GSCA model and compare measurement and structural model estimates to strengthen the robustness of their findings (Sarstedt et al. 2024a; Sharma et al. 2024).

Future extensions of the SmartPLS software's CB-SEM module could support important additional techniques, such as the predictive model assessments and the comparison of alternative (theorized) models. Also, future versions of the SmartPLS software could include features showing how changes to the model might improve the model fit. Currently, the SmartPLS software does not support model re-specification searches by modification indices, which Hair et al. (2019, Chap. 11) discuss. However, the authors of this article caution that such analyses, although popular among some in the CB-SEM community, should be approached with great care (i.e., all model inferences should ultimately be based on a solid theoretical foundations) as all modifications after seeing the results likely lead to overfitting the model to the sample data and therefore limiting the generalizability of the findings (MacCallum et al. 1992).

Acknowledgements This article uses and discusses the statistical software SmartPLS (https://www.smartpls.com). Christian M. Ringle and Jan-Michael Becker acknowledge a financial interest in SmartPLS.

Funding Open Access funding enabled and organized by Projekt DEAL.

Data availability The data utilized in this article is accessible at the following link: https://www.smartpls.com/documentation/sample-projects/cb-sem.

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