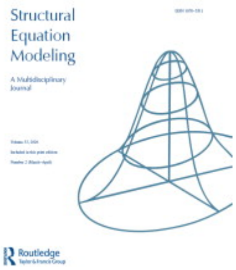

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TEACHER'S CORNER

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Consistent Partial Least Squares Structural Equation Modeling Using SmartPLS

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ABSTRACT

This *Teacher's Corner* article provides a comprehensive illustration of consistent partial least squares structural equation modeling (PLSc-SEM), a variant of the original PLS-SEM method, which corrects construct correlations for attenuation. The method thereby allows estimating common factor models within a composite-based SEM framework. Our descriptions draw on SmartPLS 4, the most frequently used software for conducting PLS-SEM analyses, illustrating how to set up and estimate the model and interpret the estimates. We further contrast our results with those from other composite-based SEM estimators and from covariance-based SEM using maximum likelihood estimation, as implemented in SmartPLS.

KEYWORDS

Consistent partial least squares path modeling; consistent partial least squares structural equation modeling; PLSc-SEM; SmartPLS; tutorial

1. Introduction

Structural equation modeling (SEM) is a widely used multivariate analysis method in the behavioral, educational, medical, and social sciences (e.g., Marcoulides & Kyriakides, 2010) to estimate complex interrelationships between constructs (i.e., latent variables) and their indicator variables (e.g., Marcoulides & Schumacker, 1996; Raykov & Marcoulides, 2006). Over the last decades, SEM has evolved into two conceptually distinct yet complementary domains: factor-based SEM, also referred to as covariance-based SEM (CB-SEM; Jöreskog, 1978, 1982) and component-based SEM (e.g., Hwang & Takane, 2004; Wold, 1974).

In factor-based SEM, theoretical concepts are typically represented as common factors, which capture the common variance shared by observed variables (Rigdon, 1998). Conversely, in component-based SEM, theoretical concepts are represented as weighted composites or components of observed variables (Marcoulides et al., 2012).[1] It is well known that both SEM approaches yield consistent estimates when applied to models that align with their ontological assumptions but produce biased estimates under model–assumption mismatch (Marcoulides & Chin, 2013). For example, component-based SEM methods, such as partial least squares SEM (PLS-SEM; Hair et al., 2025; Lohmöller, 1989; Wold, 1982),[2] produce positively biased estimates of factor loadings and negatively biased path coefficient estimates in common factor models (e.g., Dijkstra, 2010; Hwang et al., 2010; Reinartz et al., 2009). In contrast, factor-based SEM produces negatively biased estimates of indicator weights and positively biased path coefficient estimates in component models (e.g., Cho, Sarstedt, et al., 2022; Rhemtulla et al., 2020).

Addressing the biases of component-based methods in common factor models, Dijkstra and Henseler (2015) introduced consistent PLS-SEM (PLSc-SEM),[3] a variant of the original PLS-SEM method, which uses Dijkstra's (2014) composite reliability coefficient ρ_A to correct construct correlations for attenuation (see also Dijkstra & Schermelleh-Engel, 2014). PLSc-SEM yields consistent estimates of factor loadings and structural path coefficients under common factor models, while preserving the component-based nature of PLS-SEM. PLSc-SEM thereby narrows the gap between component-based and factor-based SEM approaches (Hair, Hult, et al., 2026, Chapter 8).[4]

Although standard PLS-SEM has seen widespread adoption across the social sciences and numerous other scientific fields—such as engineering, environmental sciences, and medicine—applications of PLSc-SEM remain nascent (e.g., Sabol et al., 2023; Sarstedt et al., 2022; Wang et al., 2024).

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[1] In line with, for instance, Guenther et al. (2023), Hwang et al. (2020) and Sarstedt et al. (2024), we use the terms composites and components interchangeably in this research.

[2] In the literature, PLS-SEM (e.g., Hair et al., 2011; Ringle et al., 2023; Sarstedt et al., 2023) is also referred to as path models with latent variables (Wold, 1975), partial least squares (PLS; Wold, 1985), latent variable path modeling with partial least squares (Lohmöller, 1989), PLS path modeling (e.g., Esposito Vinzi et al., 2010; Tenenhaus et al., 2005), and the PLS approach to structural equation modeling (e.g., Chin, 1998).

[3] While we use the abbreviation PLSc-SEM for consistency throughout this article (see, for example, Hair, Hult, et al., 2026), Dijkstra and Henseler (2015) simply refer to PLSc.

[4] Huang (2013) introduced a variant of PLSc-SEM, which applies Browne's (1973) generalized least squares covariance structure estimation methodology to produce consistent and efficient model estimates (see Bentler & Huang, 2014).

This may come as a surprise considering that some researchers have criticized the standard practice of estimating reflective measurement models—which they equate with common factor models—with PLS-SEM, instead of using a consistent counterpart (e.g., Henseler et al., 2016, 2025; Rönkkö et al., 2023).[5]

In response to this concern, this *Teacher's Corner* article provides a comprehensive illustration of PLSc-SEM analyses using SmartPLS 4 (Ringle et al., 2024), the most frequently used software for conducting PLS-SEM analyses (e.g., Sarstedt et al., 2022; Shela et al., 2023; Zeng et al., 2021). Software reviews emphasize the software's ease of use, such as Cheah et al. (2024, p. 105), who conclude that "SmartPLS remains the most comprehensive software for performing PLS-SEM analyses and is the preferred choice among business field researchers due to its user-friendly interface, ease of use, and continuous introduction of innovative features." Building on earlier demonstrations that have relied on the standard PLS-SEM algorithm (Hair, Hult, et al., 2026; Ramayah et al., 2018; Sarstedt et al., 2025), this article is the first to offer a step-by-step illustration on how to specify, estimate, and report models with PLSc-SEM using SmartPLS. We also briefly contrast our results with those obtained using the SmartPLS software's CB-SEM module (Hair et al., 2025), which implements maximum likelihood estimation (e.g., Jöreskog, 1978) and yields results identical to the IBM SPSS AMOS outcomes reported in Hair, Black, et al. (2019), who introduced the employee retention case study used in our illustrations. In addition, we compare our results with those generated using other component-based methods implemented in SmartPLS. We conclude with a brief discussion of some key features of PLSc-SEM and their implications for the method's future use.

2. SmartPLS Software Illustration of PLSc-SEM

2.1. Model and Data

Our software illustration draws on Hair, Black, et al. (2019, Chapter 13) employee retention model. The overall objective of this model is to explain the effects of organizational commitment (*OC*) and job satisfaction (*JS*) on employees' staying intentions (*SI*). Furthermore, the model includes work environment perceptions (*EP*) and attitudes toward coworkers (*AC*) as antecedent (exogenous) constructs influencing *OC* and *JS*. These five constructs are measured by a total of 21 reflective indicators (Figure 3)—see Hair, Black, et al. (2019, Chapter 13) for a detailed description of the dataset and model. Table A1 in the Appendix presents detailed descriptions of each item.

The data are synthetic and emulate employee survey responses collected by an established marketing research firm. Specifically, the dataset comprises $N = 400$ observations from HBAT Industries (HBAT), an international manufacturer of paper products.[6] The data were generated to satisfy the standard assumptions of factor-based SEM, including multivariate normality and, to a reasonable degree, homoskedasticity. Hair et al. (2025) used the same model and dataset to illustrate SmartPLS' CB-SEM module, which applies maximum likelihood to estimate common factor models. SmartPLS 4 also offers various other estimators, including standard PLS-SEM, generalized structured component analysis (GSCA; Hwang et al., 2024; Hwang & Takane, 2004, 2014), and sum scores regression (e.g., Hair et al., 2024). Our illustration focuses on PLSc-SEM and briefly contrasts the estimates with those obtained by CB-SEM, GSCA, PLS-SEM, and sum scores regression in SmartPLS.

2.2. Create a New Project and Import Data

When launching SmartPLS for the first time, users are prompted to select a workspace folder, which serves as the central directory for creating, opening, and updating SmartPLS projects, including models and data files. The workspace folder can be located either on the user's local drive or in a cloud-based directory, thereby allowing for access from multiple devices and locations.

Once the workspace folder has been selected, SmartPLS shows the workspace view, which lists prior projects and allows users to select from multiple sample projects, including the employee retention model and dataset that we draw upon. To create a new project, select *New Project* from the menu bar, enter a clear and descriptive name (for example, *Employee Retention* or *ER*), and save your changes. The project will then appear in the workspace. Once the project has been created, the next steps are to (1) import the data file and (2) build the model.

SmartPLS supports a variety of file formats, including comma-separated values (.csv), text files (.txt), IBM SPSS files (.sav), and Microsoft Excel files (.xls, .xlsx), thereby dispensing with the need for prior data conversion. In addition, users can import correlation or covariance matrices. To import a dataset, users must first create or select an existing project. The dataset can then be imported by right-clicking the project name, selecting the *Import data file* option from the menu, locating the relevant data file, and clicking *Open*. The software then shows the data view, where users can review and set the dataset's properties before completing the import. SmartPLS automatically identifies the first row of the data file as containing indicator names. If indicator names are not provided, the software assigns generic labels by default. Each subsequent row should contain numeric values representing individual observations, with one row per case. During the data import, SmartPLS treats empty cells as missing values; alternatively, you may specify a numeric code (e.g., −99) to indicate missing values.

Following the data import, users need to define the measurement scale type for each observed variable (i.e.,

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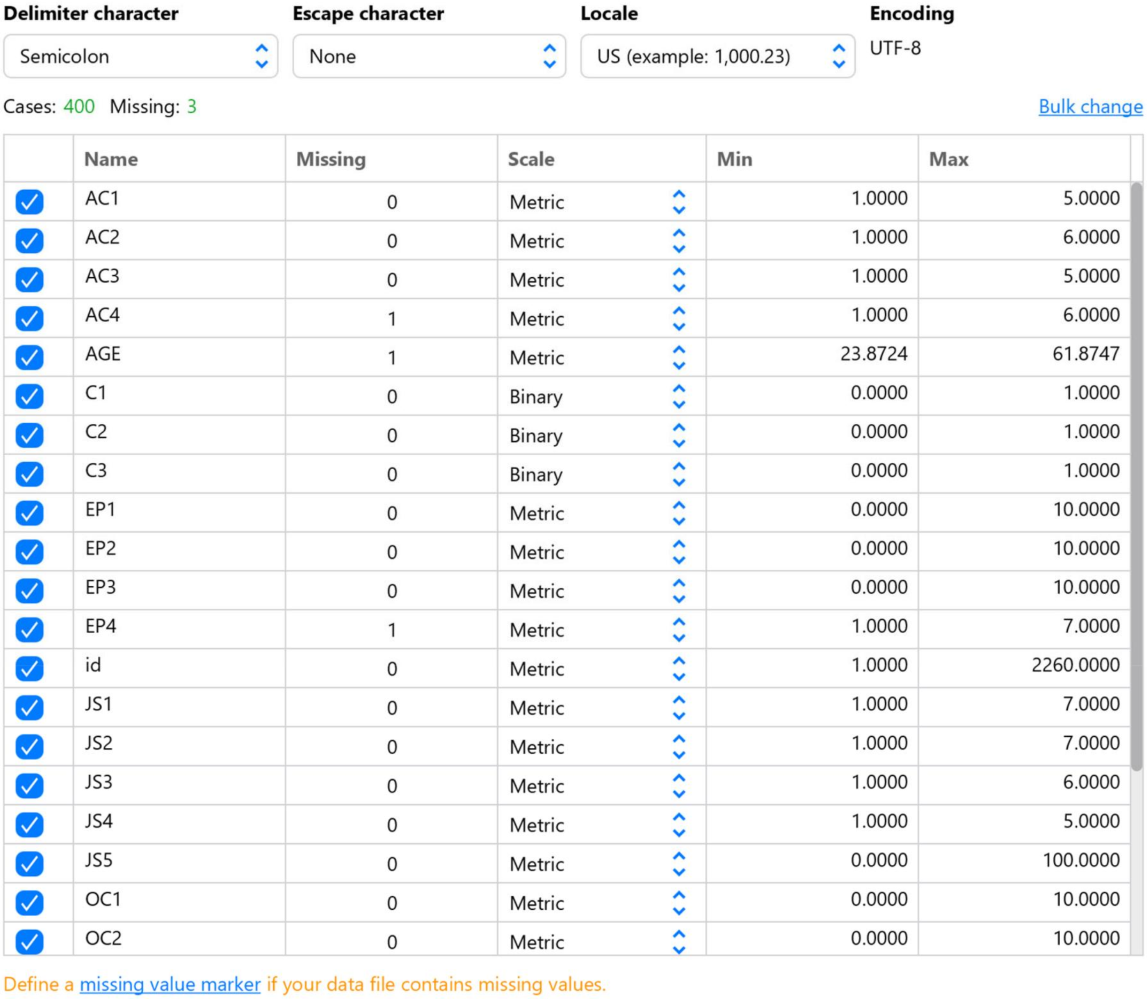
[5] Note that other researchers—including the authors of this article—call for differentiating the model estimation perspective (i.e., the way the method computes proxies of the concepts using either common factor- or composite-based SEM) and the measurement-theoretic perspective (i.e., deciding whether to specify a construct reflectively or formatively). We do not reiterate the discussion here, but refer to Guenther et al. (2025) and Sarstedt et al. (2016).

[6] The HBAT dataset is publicly available at: https://www.smartpls.com/documentation/sample-projects/employee-retention.



Delimiter character: Semicolon
Escape character: None
Locale: US (example: 1,000.23)
Encoding: UTF-8

Cases: 400 Missing: 3

Bulk change

	Name	Missing	Scale	Min	Max
☑	AC1	0	Metric	1.0000	5.0000
☑	AC2	0	Metric	1.0000	6.0000
☑	AC3	0	Metric	1.0000	5.0000
☑	AC4	1	Metric	1.0000	6.0000
☑	AGE	1	Metric	23.8724	61.8747
☑	C1	0	Binary	0.0000	1.0000
☑	C2	0	Binary	0.0000	1.0000
☑	C3	0	Binary	0.0000	1.0000
☑	EP1	0	Metric	0.0000	10.0000
☑	EP2	0	Metric	0.0000	10.0000
☑	EP3	0	Metric	0.0000	10.0000
☑	EP4	1	Metric	1.0000	7.0000
☑	id	0	Metric	1.0000	2260.0000
☑	JS1	0	Metric	1.0000	7.0000
☑	JS2	0	Metric	1.0000	7.0000
☑	JS3	0	Metric	1.0000	6.0000
☑	JS4	0	Metric	1.0000	5.0000
☑	JS5	0	Metric	0.0000	100.0000
☑	OC1	0	Metric	0.0000	10.0000
☑	OC2	0	Metric	0.0000	10.0000

Define a missing value marker if your data file contains missing values.

Figure 1. Data setup options in SmartPLS.

metric, ordinal, categorical, or binary) and may rename indicators using the *Setup* option in the SmartPLS data view (Figure 1). SEM applications typically draw on metric (or ordinal) data (e.g., Ringle et al., 2023), but users may also consider binary variables—such as when modeling moderators (Becker et al., 2023) or analyzing data from discrete choice experiments (Hair, Ringle, et al., 2019).

After the data are imported, SmartPLS automatically opens the data view (Figure 2), which displays descriptive statistics for each indicator, including the mean, standard deviation, skewness, and kurtosis. These statistics are useful for assessing data normality and identifying potential outliers or data entry errors. Users can access the data view at any time by double-clicking the dataset in the SmartPLS workspace.

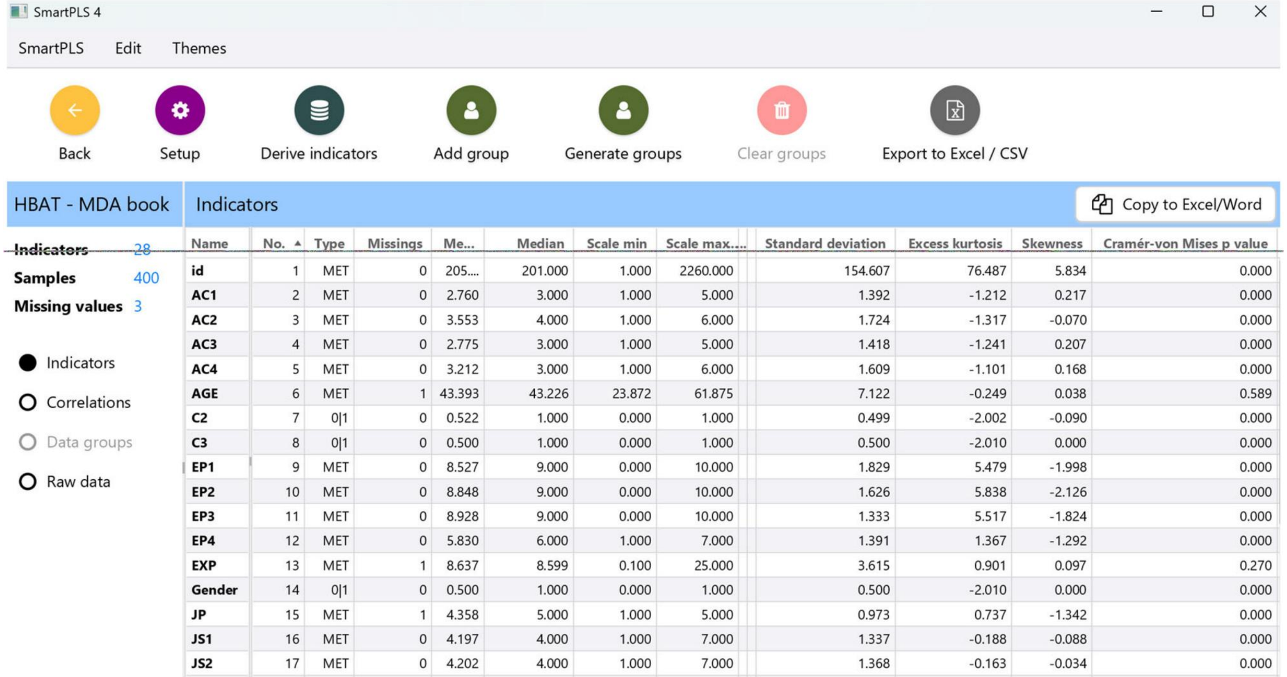
2.3. Model Creation

To create a model, users must switch to the software's modeling view by double-clicking on the model in the workspace. Model creation begins by dragging indicators from the list in the left-hand panel and dropping them onto the modeling canvas (e.g., indicators *AC1–AC4* for the *AC* construct). A new construct appears, and the software asks the user to assign it a name (e.g., *AC*). This process is repeated for the remaining constructs until all constructs shown in Figure 3 appear on the modeling canvas (i.e., *AC*, *EP*, *JS*, *OC*, and *SI)*. Constructs and indicators can be positioned using the alignment tools or adjusted manually to improve their visual presentation on the modeling canvas.

To specify relationships between constructs, users need to click the *Connect* button in the menu bar. The procedure involves selecting the source construct first and then the target construct, which draws directional arrows representing the hypothesized paths. Once this step is completed, SmartPLS displays the constructs together with their measurement models and the structural model relationships, as illustrated in Figure 3.

2.4. Model Estimation

Once the model specification is complete, it can be estimated using one of the estimators available in SmartPLS. To estimate the model with the PLSc-SEM algorithm, navigate to *Calculate* → *Consistent PLS-SEM algorithm* → *Start calculation* in the menu bar at the top of the SmartPLS interface. Alternatively, the estimation process can be initiated by clicking the *Calculate* wheel icon in the menu bar. The analysis applies algorithm default settings, but users may adjust



Indicators 28
Samples 400
Missing values 3

Name	No.	Type	Missings	Me...	Median	Scale min	Scale max....	Standard deviation	Excess kurtosis	Skewness	Cramér-von Mises p value
id	1	MET	0	205....	201.000	1.000	2260.000	154.607	76.487	5.834	0.000
AC1	2	MET	0	2.760	3.000	1.000	5.000	1.392	-1.212	0.217	0.000
AC2	3	MET	0	3.553	4.000	1.000	6.000	1.724	-1.317	-0.070	0.000
AC3	4	MET	0	2.775	3.000	1.000	5.000	1.418	-1.241	0.207	0.000
AC4	5	MET	0	3.212	3.000	1.000	6.000	1.609	-1.101	0.168	0.000
AGE	6	MET	1	43.393	43.226	23.872	61.875	7.122	-0.249	0.038	0.589
C2	7	0|1	0	0.522	1.000	0.000	1.000	0.499	-2.002	-0.090	0.000
C3	8	0|1	0	0.500	1.000	0.000	1.000	0.500	-2.010	0.000	0.000
EP1	9	MET	0	8.527	9.000	0.000	10.000	1.829	5.479	-1.998	0.000
EP2	10	MET	0	8.848	9.000	0.000	10.000	1.626	5.838	-2.126	0.000
EP3	11	MET	0	8.928	9.000	0.000	10.000	1.333	5.517	-1.824	0.000
EP4	12	MET	0	5.830	6.000	1.000	7.000	1.391	1.367	-1.292	0.000
EXP	13	MET	1	8.637	8.599	0.100	25.000	3.615	0.901	0.097	0.270
Gender	14	0|1	0	0.500	1.000	0.000	1.000	0.500	-2.010	0.000	0.000
JP	15	MET	1	4.358	5.000	1.000	5.000	0.973	0.737	-1.342	0.000
JS1	16	MET	0	4.197	4.000	1.000	7.000	1.337	-0.188	-0.088	0.000
JS2	17	MET	0	4.202	4.000	1.000	7.000	1.368	-0.163	-0.034	0.000

Figure 2. SmartPLS data view.

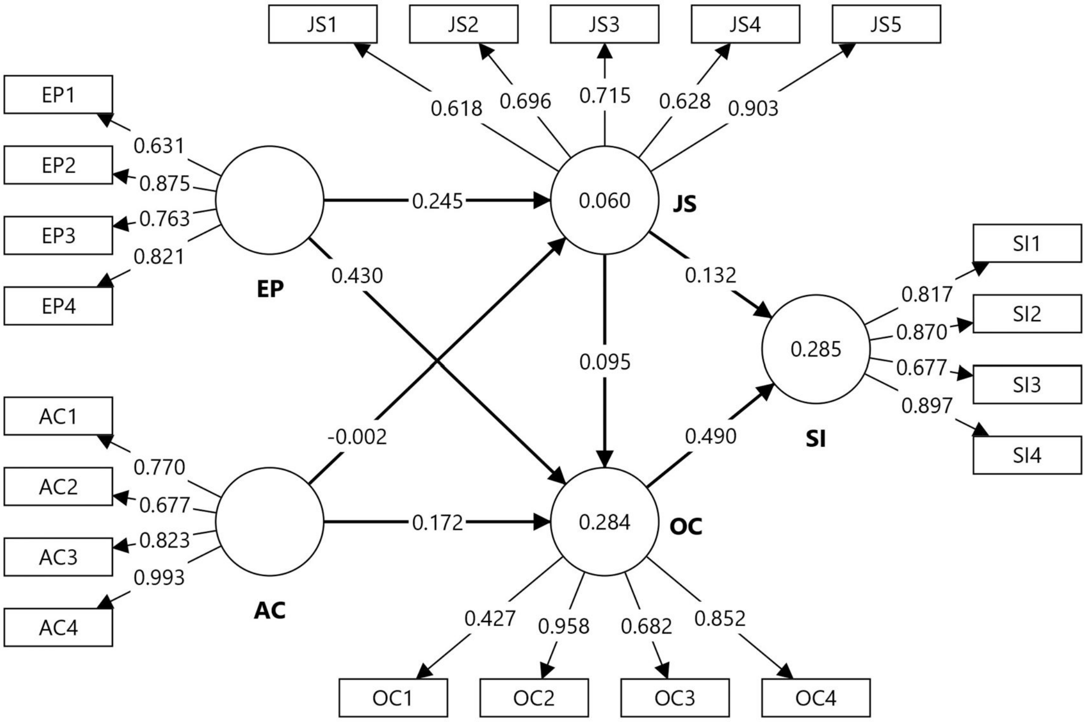


Figure 3. Employee retention model in SmartPLS.
Note: To ensure a parsimonious use of figures, we present the model with results at this stage, as obtained in SmartPLS after model estimation; these results will be discussed in detail in Sections 2.5 and 2.6

the settings by using a different weighting scheme, manually set initial weights, or request unstandardized results (Tenenhaus et al., 2005).

Upon conversion, SmartPLS automatically generates a detailed results report, which includes key outputs for measurement model evaluation and structural model assessment. The results can be reviewed directly within the software interface and exported or saved for further analysis and documentation. For example, results for internal consistency reliability (i.e., Cronbach's α, ρ_A, and ρ_C), convergent validity (i.e., average variance extracted, AVE), and discriminant validity (i.e., the Fornell–Larcker criterion and the HTMT criterion) can be accessed by navigating to the *Quality criteria* section of the results report. Under *Final results* → *Outer loadings*, users can inspect indicator loadings, which are also shown in the graphical output (Figure 3).

Table 1. Reflective measurement model assessment results.

Construct	Item	Outer loading	Cronbach's α	Composite reliability (ρA)	Composite reliability (ρC)	Average variance extracted (AVE)
AC	AC1	0.770	0.894	0.911	0.926	0.679
	AC2	0.677				
	AC3	0.823				
	AC4	0.993				
EP	EP1	0.631	0.857	0.869	0.903	0.605
	EP2	0.875				
	EP3	0.763				
	EP4	0.821				
JS	JS1	0.618	0.844	0.856	0.888	0.518
	JS2	0.696				
	JS3	0.715				
	JS4	0.628				
	JS5	0.903				
OC	OC1	0.427	0.832	0.887	0.886	0.573
	OC2	0.958				
	OC3	0.682				
	OC4	0.852				
SI	SI1	0.817	0.889	0.899	0.923	0.672
	SI2	0.870				
	SI3	0.677				
	SI4	0.897				

Note: AC: attitudes toward coworkers; *EP:* environment perceptions; *JS:* job satisfaction; *OC:* organizational commitment; *SI:* staying intentions.

Table 2. HTMT criterion results.

Construct	AC	EP	JS	OC
EP	0.257 [0.163; 0.347]			
JS	0.066 [0.032; 0.075]	0.244 [0.164; 0.326]		
OC	0.275 [0.195; 0.355]	0.495 [0.405; 0.580]	0.209 [0.118; 0.297]	
SI	0.310 [0.222; 0.395]	0.569 [0.471; 0.656]	0.232 [0.154; 0.313]	0.501 [0.410; 0.586]

Notes: AC: attitudes toward coworkers; *EP:* environment perceptions; *JS:* job satisfaction; *OC:* organizational commitment; *SI:* staying intentions. Values in brackets: 90% bias-corrected bootstrap confidence intervals (obtained by using the percentile approach and 10,000 subsamples).

Users may also run inference tests for model assessment criteria, for example, to examine whether the HTMT outcomes (Henseler et al., 2015; see also Ringle et al., 2023) differ significantly from a specified threshold (Franke & Sarstedt, 2019). This assessment requires the computation of bootstrap confidence intervals, which can be obtained by executing the bootstrapping procedure in SmartPLS. To initiate this procedure, return to the modeling window and select *Calculate → Consistent PLS-SEM bootstrapping*. In the dialog box that opens, select 10,000 subsamples and choose the complete bootstrapping option, which ensures that all statistics are being bootstrapped, including the HTMT. Under *Advanced settings*, select the percentile bootstrap confidence intervals and specify a one-tailed test with a significance level of 0.05. The results obtained under these conditions are equivalent to those of a two-tailed test with a significance level of 0.10. After confirming these settings, proceed by clicking the *Start calculation* button to initiate the bootstrapping process. Upon completion, navigate to *Quality criteria → Heterotrait–monotrait ratio (HTMT)*. The corresponding table displays the original HTMT values (listed under the original sample column) for each construct pair, alongside the mean HTMT values computed from the 10,000 bootstrap samples (shown in the sample mean column). The last two columns report the 5th and 95th percentiles of the percentile bootstrap results. The upper bound (95th percentile) should be lower than the HTMT cutoff value of 0.85 (or 0.90), indicating that the HTMT value is significantly below this threshold (Hair, Hult, et al., 2026; Chapter 4)—see Section 2.5 for the results discussion.

2.5. Measurement Model Assessment

The next step involves assessing the measurement model results, following the guidelines that Hair, Hult, et al. (2026) and Sarstedt et al. (2025) report for standard PLS-SEM model estimation. The results in Table 1 indicate that all measures meet the commonly accepted thresholds for internal consistency reliability, convergent validity, and discriminant validity. While some outer loadings (e.g., *OC1*) are slightly below the recommended threshold of 0.708, these indicators are retained because all constructs exhibited composite reliability (ρ_A) values greater than 0.70 and AVE values exceeding 0.50 (Hair, Hult, et al., 2026, Chapter 4). In addition, retaining these items ensures the preservation of the measures' content validity.

Moreover, the results of the HTMT analysis (Table 2) reveal that none of the upper bounds of the 90% (bias-corrected) percentile bootstrap confidence intervals (i.e., the 95th percentile) exceeded the threshold value of 0.85. These findings collectively support the reliability and validity of the measurement models.

2.6. Structural Model Assessment

The first step in structural model assessment involves checking for collinearity issues among the predictor constructs by

Table 3. Structural model assessment results.

Relationship	Path coefficient	Standard deviation	*t* value	*p* value	CI	VIF	f^2
AC → JS	−0.002	0.058	0.043	.966	[−0.119; 0.106]	1.055	0.000
AC → OC	0.172	0.048	3.619	.000	[0.078; 0.264]	1.055	0.039
EP → JS	0.245	0.053	4.641	.000	[0.136; 0.343]	1.055	0.060
EP → OC	0.430	0.059	7.272	.000	[0.309; 0.540]	1.101	0.227
JS → OC	0.095	0.052	1.820	.069	[−0.011; 0.194]	1.047	0.012
JS → SI	0.132	0.046	2.833	.005	[0.043; 0.225]	1.035	0.023
OC → SI	0.490	0.051	9.520	.000	[0.386; 0.587]	1.035	0.321

Note: AC: attitudes toward coworkers; *EP:* environment perceptions; *JS:* job satisfaction; *OC:* organizational commitment; *SI:* staying intentions; CI: 95% bias-corrected percentile bootstrap confidence interval of the path coefficient, with the 2.5th percentile as the lower bound and the 97.5th percentile as the upper bound, obtained using the percentile bootstrap approach with 10,000 subsamples.

Table 4. Model fit statistics for PLSc-SEM estimation.

	Saturated model	Estimated model
SRMR	0.044	0.071
d_{ULS}	0.438; $UB_{95\%}$: 0.636	1.155; $UB_{95\%}$: 0.641
d_G	0.303; $UB_{95\%}$: 0.953	0.330; $UB_{95\%}$: 0.870
χ^2	723.907	772.032
NFI	0.837	0.826

Notes: SmartPLS uses Bollen-Stine bootstrapping to provide the results at the 95th percentile ($UB_{95\%}$) for the model fit statistics. We use percentile bootstrapping with 10,000 subsamples and the complete (slower) option in SmartPLS.

examining their variance inflation factors (VIF; e.g., Hair, Hult, et al., 2026, Chapter 6; Sarstedt et al., 2025). To do so, navigate to *Quality criteria → Collinearity statistic (VIF)* and select either the inner model matrix or the list view under VIF values in the list. As shown in Table 3, no evidence of problematic collinearity is observed, as all VIF values are below the critical threshold of three. Hence, the structural model estimates can be interpreted without concern for multicollinearity.

To assess the effect sizes (f^2) of the structural relationships, navigate to *Quality criteria → f square → Matrix view*. As shown in Table 3, the paths from *EP* to *OC* (f^2 = 0.227) and from *OC* to *SI* (f^2 = 0.321) demonstrate medium to large effect sizes. In contrast, the relationships *EP → JS* (f^2 = 0.060), *AC → OC* (f^2 = 0.039, and *JS → SI* (f^2 = 0.023) have small effect sizes, while the relationships *AC → JS* (f^2 = 0.000) and *JS → OC* (f^2 = 0.012) involve trivial effects.

Following Schuberth et al. (2023), we also examine model fit measures as common in applications of factor-based SEM.[7] The SmartPLS results report provides the standardized root mean square residual (SRMR) under *Quality criteria → Model fit*. The estimated model yields an SRMR value of 0.071 (Table 4), which falls below the commonly recommended threshold of 0.08, thereby supporting model fit (Hu & Bentler, 1999).

In addition, researchers may apply a bootstrap-based test of model fit, which evaluates the discrepancy between the sample covariance matrix and the model-implied covariance matrix (Schuberth et al., 2023). This discrepancy is computed using the squared Euclidean distance (d_{ULS}) and the geodesic distance (d_G). The test of overall model fit originates from Beran and Srivastava (1985) and, under the null hypothesis, assumes equality between the matrices. We interpret model fit based on the Bollen–Stine (Bollen and Stine 1992) bootstrap confidence intervals for d_{ULS} and d_G, as provided by SmartPLS. The model exhibits a good fit when the confidence interval includes the original d_{ULS} and d_G values, suggesting that the discrepancy between the model-implied and empirical correlation matrices remains attributable to sampling error. To obtain these results in SmartPLS, run percentile bootstrapping with 10,000 subsamples using the *Complete (slower)* option. The results under *Model fit → d_ULS* in the SmartPLS results report show that the squared Euclidean distance of the estimated model equals 1.155, which exceeds the bootstrap-based 95th percentile of 0.641. This result therefore does not support model fit (Table 4). In contrast, the geodesic distance of the estimated model under *Model fit → d_G* equals 0.330, which falls below the bootstrap 95th percentile of 0.870 (Table 4). Thus, the bootstrap-based test based on d_G supports model fit.

Taken together, the results provide mixed evidence regarding the model's overall fit. While the bootstrap-based test yields conflicting conclusions—rejecting model fit based on the squared Euclidean distance (d_{ULS}) but supporting model fit based on the geodesic distance (d_G)—the SRMR value falls below the threshold of 0.08. Given the established use and interpretability of SRMR in factor-based SEM, these findings suggest that the estimated model exhibits an overall satisfactory level of fit.

Finally, to analyze the structural relationships in the model, return to the modeling view and select *Calculate → Consistent PLS-SEM bootstrapping → Start calculation* to obtain bootstrap estimates. Note that you may use the default settings with the *Most important (faster)* option, along with the percentile bootstrap, a two-tailed significance test at the 0.05 significance level, and fixed seed. However, users should increase the number of bootstrap subsamples from 5,000 to 10,000 to ensure stable estimates (Hair, Hult, et al., 2026, Chapter 5). The resulting path coefficients and their corresponding confidence intervals are available in the results report under *Final results → Path coefficients*. Based on the 95% bias-corrected percentile bootstrap confidence intervals (Table 3), all structural relationships are statistically significant, except for the relationships between *AC* and *JS* as well as between *JS* and *OC*. Specifically, *EP* has a substantial positive effect on *JS* ($\beta = 0.245$), whereas *AC* does not exert a significant influence on *JS* ($\beta = -0.002$). Furthermore, *AC* ($\beta = 0.172$), *EP* ($\beta = 0.430$), and *JS* ($\beta = 0.095$) confirm positive effects on *OC*. Likewise, both *JS* ($\beta = 0.132$) and *OC* ($\beta = 0.490$) positively influence *SI*.

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[7] Note that model fit has been controversially discussed in composite-based SEM (e.g., Lohmöller, 1989, Chapters 2 and 5; Sarstedt et al., 2025).

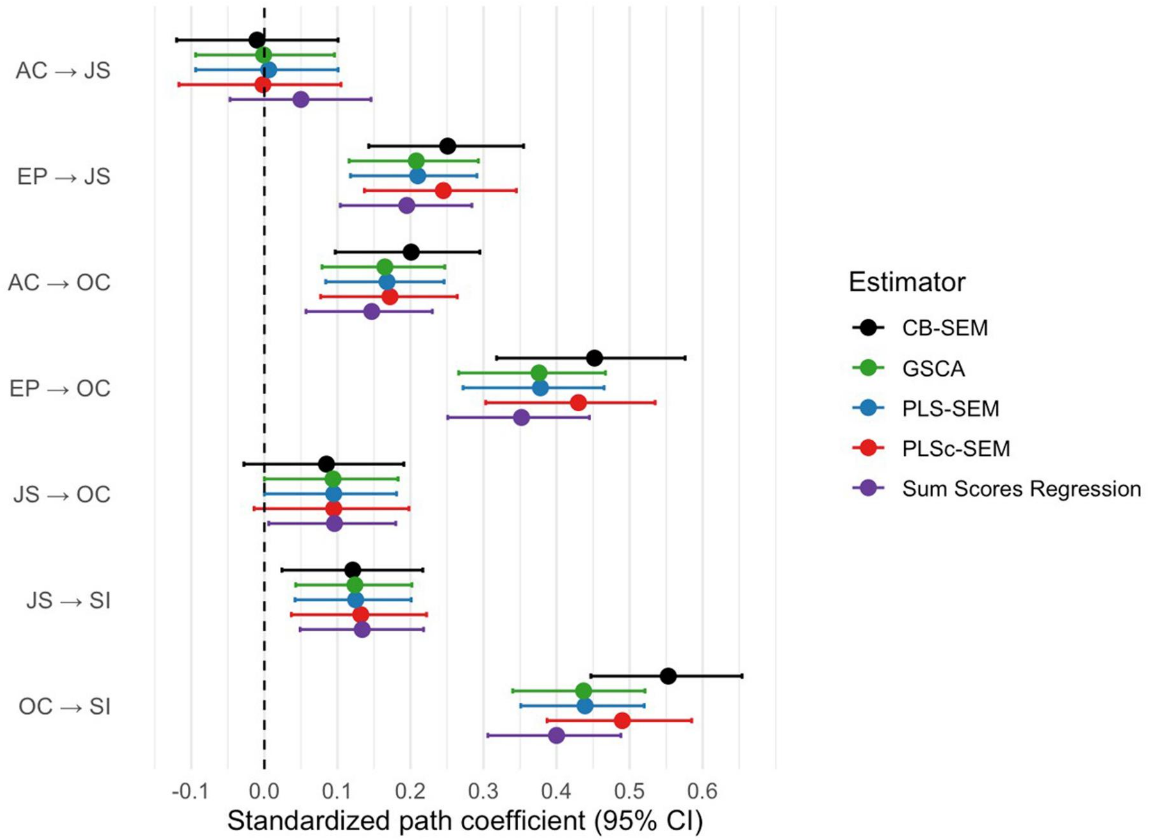

Figure 4. Multimethod model estimation results for structural model of the employee retention example.
Note: The figure shows the standardized path coefficients and their 95% bootstrap confidence intervals across methods; *AC:* attitudes toward coworkers; *EP:* environment perceptions; *JS:* job satisfaction; *OC:* organizational commitment; *SI:* staying intentions

3. Alternative Model Estimation Results

Methodological research in the SEM domain has emphasized that the choice of estimation method can substantially influence statistical results, even when the underlying model structure and dataset remain constant (Sarstedt et al., 2024). We therefore evaluate the stability and robustness of our previous results using alternative estimators implemented in the SmartPLS software, namely CB-SEM (i.e., using maximum likelihood estimation), GSCA, standard PLS-SEM, and sum scores regression, which involves computing average composite scores for each construct that are subsequently used as input for multiple regression analysis (Hair et al., 2024).

The results in Figure 4 show that the structural model point estimates and confidence intervals of all the methods generally align (see also Figures A1 to A4 in the Appendix). Particularly, PLS-SEM and GSCA results are almost identical, while sum scores regression shows more variability. In line with simulation evidence comparing the two methods (Dijkstra & Henseler, 2015), CB-SEM and PLSc-SEM results correspond closely with slightly increased variation in the relationship between *OC* and *SI*.[8] Comparing the results, however, the core structural relationships and theoretical interpretations remained consistent across estimation methods (see also Sarstedt et al., 2024). Similarly, CB-SEM-based model fit assessment suggests that the model fits well (Table A2), thereby supporting the conclusions drawn from the PLSc-SEM analysis (Table 4). Compared to the structural model results, the measurement model estimates show much greater variability. Particularly, the PLSc-SEM estimates are much more variable, as evidenced in wider confidence intervals (Figure A5 in the Appendix).

The adoption of a multimethod estimation strategy provides strong evidence of the model's robustness and reliability. Although slight statistical variations were observed among estimation approaches, the fundamental relationships and substantive conclusions remained intact. This methodological cross-validation reinforces the credibility of the findings and underscores the importance of employing multiple estimation techniques in SEM research. Doing so ensures empirical results are not artifacts of a particular estimation method, thereby enhancing the validity, generalizability, and methodological transparency of the research conclusions (e.g., Guenther et al., 2025; Hair, Sharma, et al., 2026; Sharma et al., 2024).

Note that the comparisons across CB-SEM, GSCA, PLS-SEM, PLSc-SEM, and sum scores regression are presented for descriptive and illustrative purposes only and are not intended to imply the superiority or general applicability of any estimation approach. As demonstrated in prior Monte Carlo simulation studies, the relative performance of factor- and component-based methods depends on the data-generating processes, model design, and measurement properties (Cho, Sarstedt, et al., 2022; Dijkstra, 2010; Hwang

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[8] The CB-SEM results generated by SmartPLS are identical to those that Hair, Black, et al. (2019) document when estimating the model and data with the IBM SPSS AMOS software.

et al., 2010; Reinartz et al., 2009; Rhemtulla et al., 2020). Accordingly, our results should be interpreted as evidence of results robustness in the confinements of the specific model and empirical setting examined here, rather than as a general claim about estimation method performance.

4. Concluding Remarks

SmartPLS provides an integrated environment for estimating structural equation models and supports multiple estimation techniques, including CB-SEM, GSCA, PLS-SEM, PLSc-SEM, and sum scores regression. In addition, the software offers a wide range of further methods and analyses, such as linear regression (including endogeneity assessment using the instrumental-variable-free Gaussian copula approach), logistic regression, path analysis, PROCESS, necessary condition analysis, confirmatory factor analysis, and principal component analysis. The SmartPLS software enables a broad set of modeling and algorithmic options and facilitates transparent reporting of model estimates (Cheah et al., 2024). Extending prior illustrations of the software (Hair, Hult, et al., 2026; Ramayah et al., 2018; Sarstedt et al., 2025), including the use of CB-SEM in SmartPLS (Hair et al., 2025), this *Teacher's Corner* article used SmartPLS to estimate models with latent variables using PLSc-SEM, a variant of PLS-SEM, which facilitates estimating common factor models.

PLSc-SEM is an appropriate method when researchers conceptualize their constructs as common factors and assume that the data stem from a common factor model population (Sarstedt et al., 2016). Evidence from Monte Carlo simulation studies indicates that, for correctly specified factor models, PLSc-SEM yields minimal bias and nearly identical parameter estimates and comparable statistical power as CB-SEM (e.g., Dijkstra & Henseler, 2015; Sarstedt et al., 2024).

From a practical perspective, PLSc-SEM retains many of the advantages commonly associated with PLS-SEM, including the absence of distributional assumptions, the ability to estimate complex models, robustness to local misspecifications, and stable convergence behavior. At the same time, users should be aware that the correction for attenuation applied in the final step of PLSc-SEM alters the original PLS-SEM path coefficients, which are optimized for maximizing explained variance. Consequently, predictive model assessments using $\mathrm{PLS}_{\mathrm{predict}}$ (Shmueli et al., 2016, 2019) and the cross-validated predictive ability test (Liengaard et al., 2021; Sharma et al., 2023), which are commonly used in applications of standard PLS-SEM, are not readily applicable in PLSc-SEM. This diminishes the method's ability to generate practical implications grounded in the model's predictive capabilities (e.g., Cho, Hwang, et al., 2022; Hair, 2021; Hair & Sarstedt, 2021; Hofman et al., 2017; Sarstedt & Danks, 2022) in favor of a stronger focus on model fit within a common factor model framework.

SmartPLS provides a versatile and user-friendly software environment for conducting PLSc-SEM analyses. As highlighted by Cheah et al. (2024), its intuitive interface, advanced visualization capabilities, and regular updates that reflect ongoing methodological developments (e.g., see, for instance, Table 1 in Gudergan et al., 2025) make it a valuable and reliable tool for applied researchers. This *Teacher's Corner* article supports scholars in effectively implementing PLSc-SEM using SmartPLS, thereby contributing to rigorous theory testing, transparent empirical practice, and the continued advancement of SEM research.

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Appendix

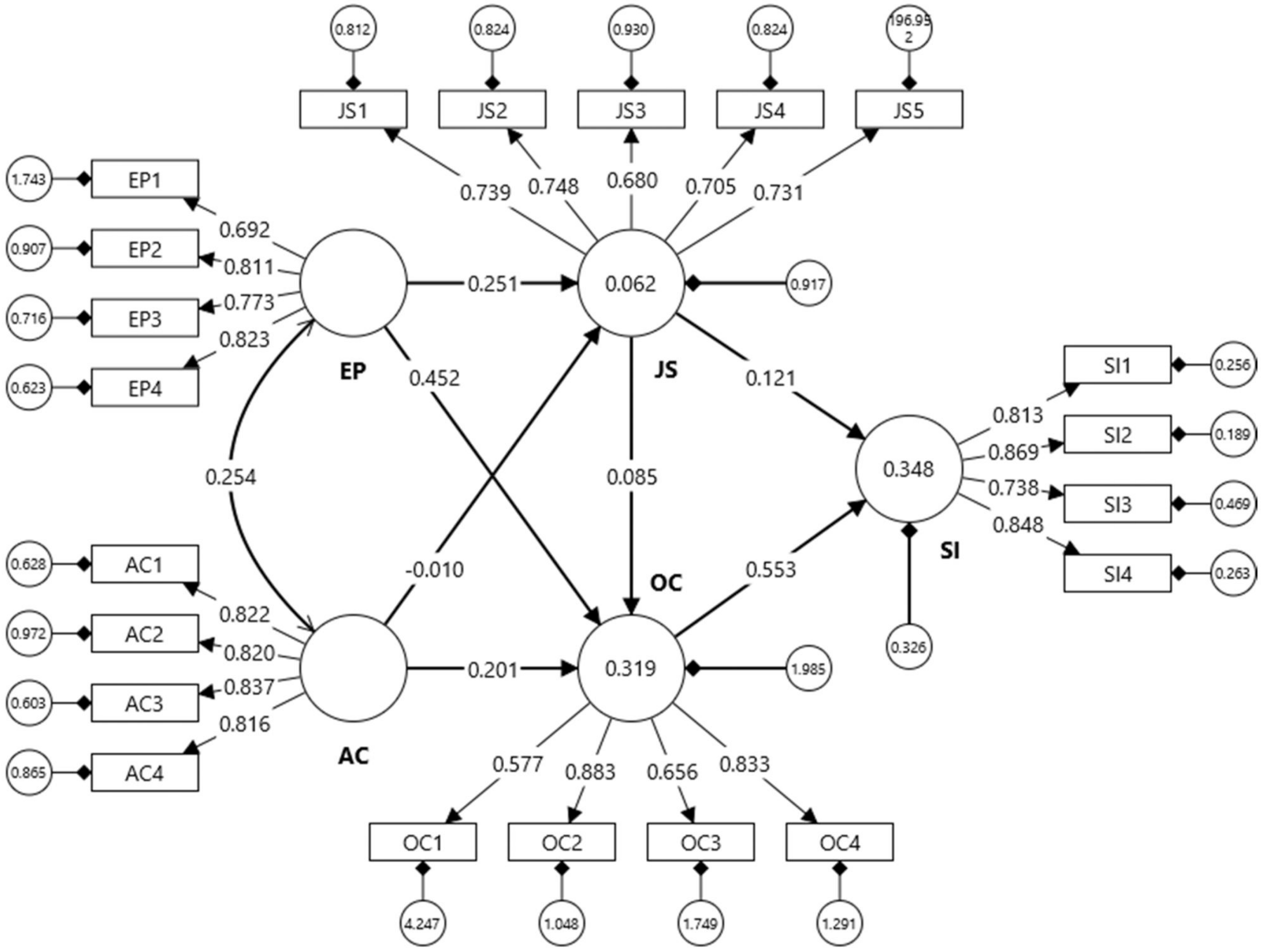

Figure A1. CB-SEM Estimation results in SmartPLS.

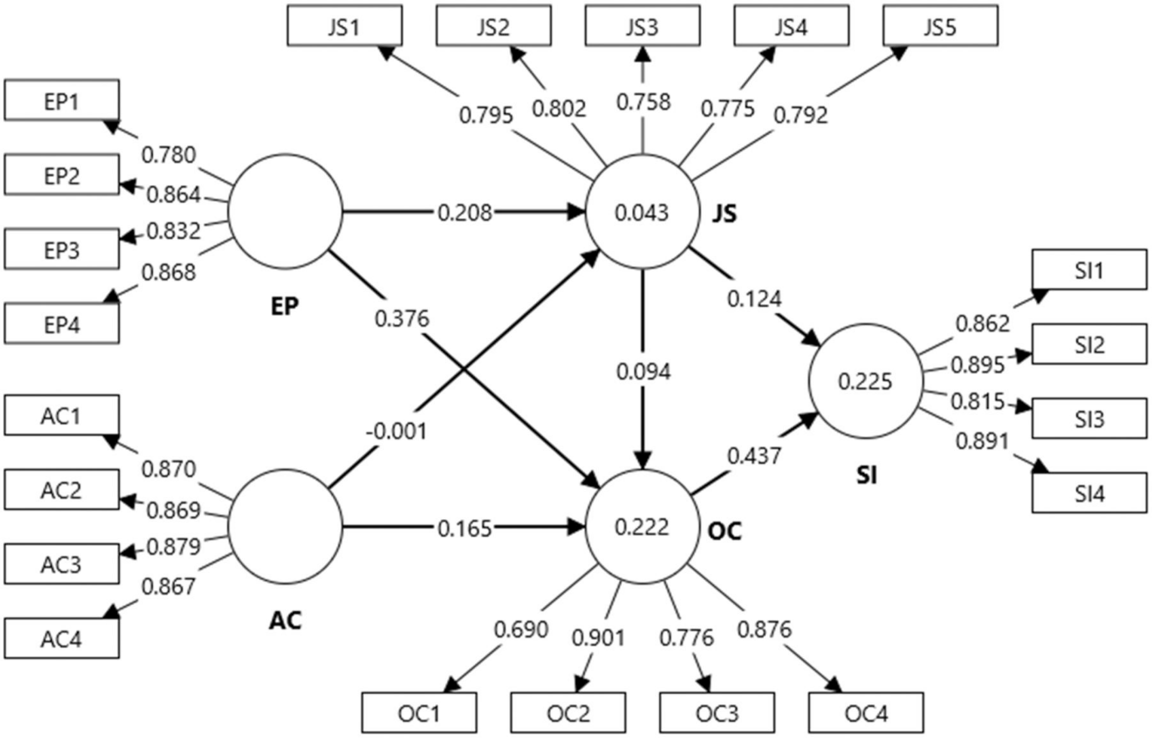

Figure A2. GSCA estimation results in SmartPLS.

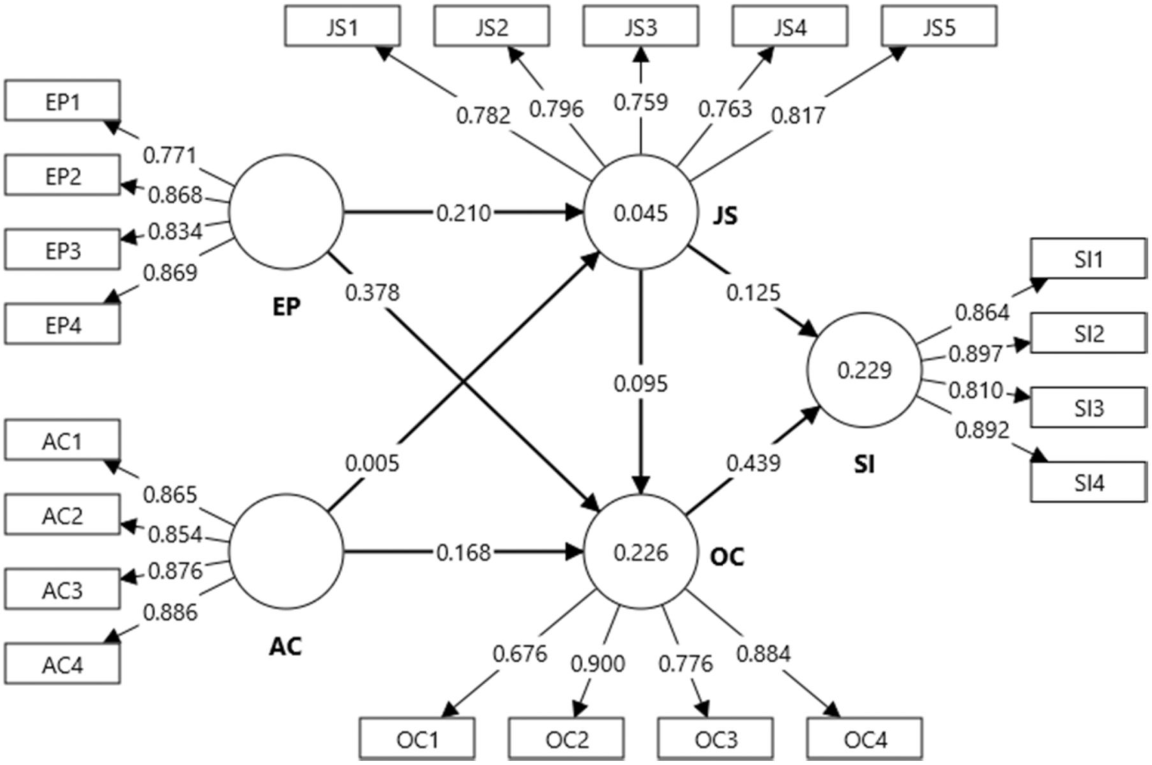

Figure A3. PLS-SEM Estimation results in SmartPLS.

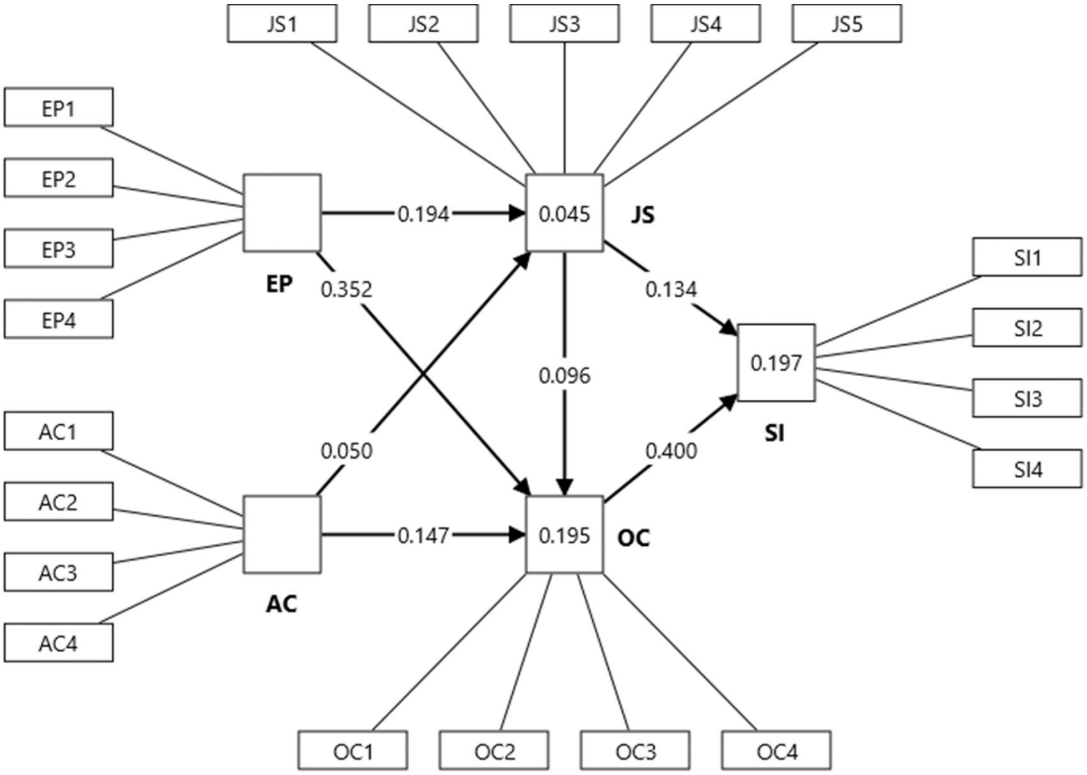

Figure A4. Sum scores regression estimation results in SmartPLS.
Note: The figure shows the standardized loading estimates and their 95% bootstrap confidence intervals across methods; *AC:* attitudes toward coworkers; *EP:* environment perceptions; *JS:* job satisfaction; *OC:* organizational commitment; *SI:* staying intentions.

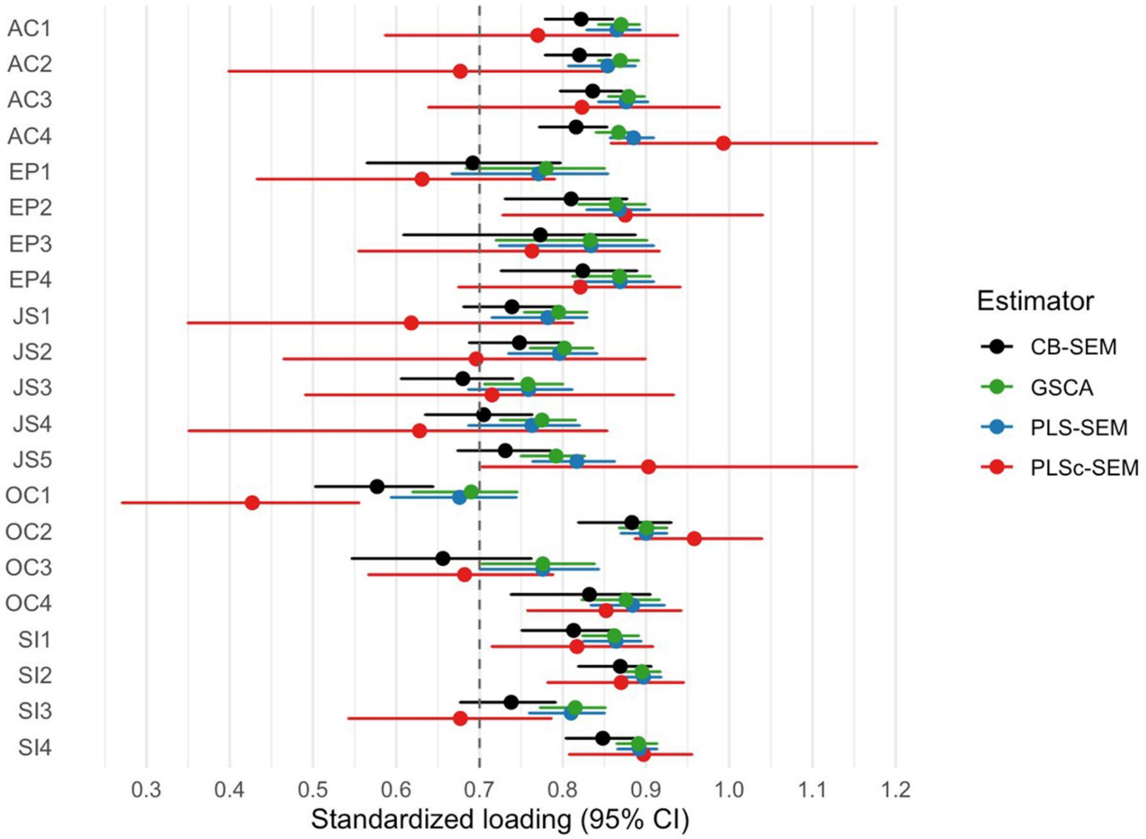

Figure A5. Multimethod model estimation results for the measurement models of the employee retention example.

Table A1. Observed indicators used in the employee retention model (adopted from Hair et al., 2019a, Table 10.2).

Construct	Item	Scale type	Description
AC	AC1	5-Point Likert	How happy are you with the work of your coworkers? *Not happy ___Somewhat happy ___ Happy ___ Very happy ___ Extremely happy*
	AC2	7-Point semantic differential	How do you feel about your coworkers? *Very unfavorable ____________ Very favorable*
	AC3	5-Point Likert	How often do you do things with your coworkers on your days off? *___ Never ___ Rarely ___ Occasionally ___ Often ___ Very often*
	AC4	6-Point semantic differential	Generally, how similar are your coworkers to you? *Very different ____________ Very similar*
EP	EP1	0–10 Likert	I am comfortable with my physical work environment at HBAT. *Strongly disagree ____________ Strongly agree*
	EP2	0–10 Likert	The place I work in is designed to help me do my job better. *Strongly disagree ____________ Strongly agree*
	EP3	0–10 Likert	There are few obstacles to make me less productive in my workplace. *Strongly disagree ____________ Strongly agree*
	EP4	7-Point Semantic Differential	What term best describes your work environment at HBAT? *Too hectic _________ Very soothing*
JS	JS1	0–10 Likert	Disagree–Agree All things considered, I feel very satisfied when I think about my job. *Strongly disagree ____________ Strongly agree*
	JS2	7-Point semantic differential	When you think of your job, how satisfied do you feel? *Not at all satisfied ____________________ Very much satisfied*
	JS3	7-Point semantic differential	How satisfied are you with your current job at HBAT? *Very unsatisfied ____________________ Very satisfied*
	JS4	7-Point semantic differential	How satisfied are you with HBAT as an employer? *___ Not at all ___ Little ___ Average ___ A lot ___ Very much*
	JS5	Percent satisfaction	Indicate your satisfaction with your current job at HBAT by placing a percentage in the blank, with *0% = Not satisfied at all, and 100% = Highly satisfied.* _________
OC	OC1	0–10 Likert	My work at HBAT gives me a sense of accomplishment. *Strongly disagree ____________ Strongly agree*
	OC2	0–10 Likert	I am willing to put in a great deal of effort beyond that normally expected to help HBAT be successful. *Strongly disagree ____________ Strongly agree*
	OC3	0–10 Likert	I have a sense of loyalty to HBAT. *Strongly disagree ____________ Strongly agree*
	OC4	0–10 Likert	I am proud to tell others that I work for HBAT. *Strongly disagree ____________ Strongly agree*
SI	SI1	5-Point Likert	I am not actively searching for another job. *Strongly disagree ____________ Strongly agree*
	SI2	5-Point Likert	I seldom look at the job listings on monster.com. *Strongly disagree ____________ Strongly agree*
	SI3	5-Point Likert	I have no interest in searching for a job in the next year. *Strongly disagree ____________ Strongly agree*
	SI4	5-Point Likert	How likely is it that you will be working at HBAT one year from today? *Very unlikely ___ Unlikely ___ Somewhat likely ___ Likely ___ Very likely*

Table A2. Model fit statistic for CB-SEM estimation.

	Estimated model	Null model
χ^2	284.520	4452.073
Number of model parameters	50	21
Number of observations	400	n/a
Degrees of freedom	181	210
p Value	0	0
χ^2/df	1.572	21.200
RMSEA	0.038	0.225
RMSEA low (90% confidence interval)	0.029	0.219
RMSEA high (90% confidence interval)	0.046	0.23
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	384.52	n/a
BIC	584.093	n/a

Note: n/a: not available.