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STRUCTURAL EQUATION MODELING: IS IT STILL WORTH LEARNING?

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Introduction

> … we are in a time when methods for understanding human behavior and development are advancing at an extraordinary pace. One side effect of this rapid advancement is that applied researchers are often limited more by their ability to understand and apply the existing methodological tools than by an absence of such tools. (Little, 2024, p. v)

Although structural equation modeling (SEM) has a long history and is a widely used method in various areas of Applied Social Sciences, it remains a challenging topic for students and new researchers, because learning requires a great effort for many years, and even more so when one has little experience with quantitative methods in general.

The lack of knowledge about this method causes researchers to avoid research problems that require this method, or, even worse, prevents them from formulating such research problems.

Despite this difficulty, the tools for estimating such models are more user-friendly, which can induce researchers to use them even when they do not fully master the method, leading to questionable results.

Even if the researcher does not intend to use this method in their research, they are likely to have to read, study, or express an opinion about an article that employs this method at some point. Still, with superficial reading, one tends to believe that the authors did a good job rather than finding research gaps.

Thus, this article **aims** to exemplify the critical reading, rereading, and estimation of an alternative model based on the data published in the article under analysis.

We hope to convince the reader that the answer to the question posed in the title is "yes", and for this, we will use as an example an article published in the journal Design Studies.

First, we will make a critical reading, comparing the hypotheses with the methods used, results obtained and we will highlight the weaknesses; secondly, we will reread considering the results that are available in the article itself; and thirdly, we will redo the tests of the hypotheses using as input the matrix of correlations available in the article itself, estimating the measurement and structural model through the modeling of structural equations based on covariances using the SmartPLS 4 software with the recently made available option (maximum likelihood) and the lavaan package of the R software.

Thus, we hope that this article will serve as a tutorial on how to **read** articles that use CB-SEM, and **how to reestimate** the model (including alternative models) from the matrix of covariances or correlations.

Although the emphasis of this article lies in the method itself, the alternative model discussed also contributes to the phenomenon under discussion: **Team Learning Behavior (TLB).**

1 Example presentation "Team Learning Behavior"

The choice of the example to be discussed occurred in an unsystematic way, as follows: the article by Tan et al. (2023) was included as a basic bibliography for one of the classes taught in a master's and doctoral course in Business Administration because it met two criteria: (i) the article deals with team learning behaviors and (ii) the journal is well qualified in general (Scimago: H = 116 = Q1 | Google metrics: H5 = 40 | JIF 2024 = 4.8 | CiteScore 2024 = 10.5 = 97th percentile in Social Science).

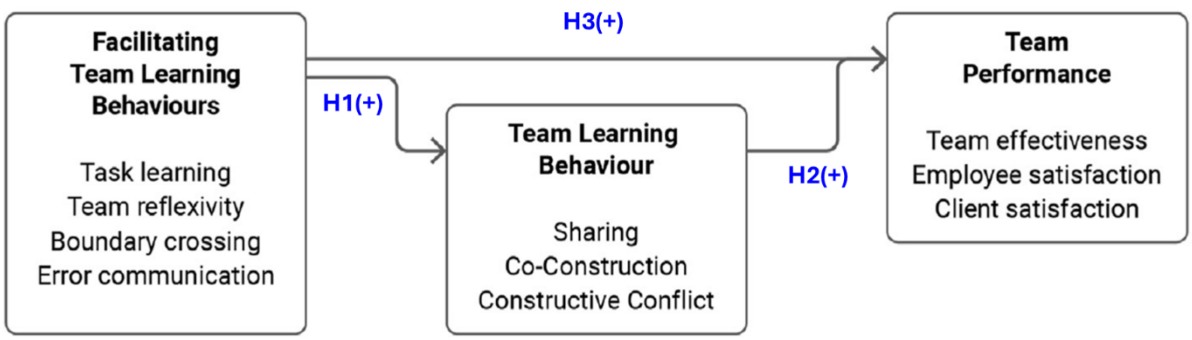
During the preparation of materials for class discussion of the article, some inconsistencies were observed (presented in the next section), which motivated the preparation of this article.

1.1 The model of Tan et al. (2003)

The model is composed of three multidimensional constructs, which are related as shown in Figure 1: (i) Facilitating Team Learning Behaviors (FTLB): Task learning, team learning, Boundary crossing, Error communication; (ii) Team learning behavior (TLB): Sharing, Co-construction, Constructive conflict; (iii) Team performance (TP): Team effectiveness, Employee satisfaction, Client satisfaction. The definitions of the constructs and their dimensions are available in the article by Tan et al. (2023, pp. 5-9) and have not been repeated here for the sake of space.

To get the most out of this article, we suggest that readers **stop here**, read pages 1 to 17 of Tan et al., reflect on the quantitative results presented by the authors (whether they agree or not, although we have given a "*spoiler*" from the beginning), and then **return here**.

Figure 1
Team Learning Behavior Model



Source: Tan et al. (2023, p.6).
Legend: Team reflexivity has two dimensions: Team reflexivity task, and Team reflexivity process.
Note: H1(+), H2(+) and H3(+) have been added.

The authors did not explain hypotheses, but Figure 1 contains arrows relating to the constructs, which can be interpreted as:

- H1(+): FTLB positively influences TLB

- H2(+): TLB positively influences TP.
- H3(+): FTLB positively influences TP.

1.2 The results of Tan et al. (2003): critical reading

We define "**critical reading**" as the process of thoroughly understanding the objectives, hypotheses, methods, and results achieved, and identifying potential problems.
→ Are the methods chosen the appropriate ones? Moreover, were they used correctly?

The article by Tan et al. consists of both quantitative and qualitative stages, including interviews. In the present research, we are discussing only the first stage.

Data collection was conducted through a survey, yielding 105 valid responses from Australian architects who have been working in teams (two or more individuals) for at least two years.

Confirmatory factor analysis was used to evaluate and adjust the measurement model of the 11 dimensions (first-order latent variables): 5 FTLB, 3 TLB, and 3 PT, so that all latent variables (LV) had Cronbach's alpha values greater than 0.75 (Table 1).

At this stage of the analysis there are **two criticisms**: (i) the standard deviation values presented in Table 1 do not seem correct because 0.04, 0.05 or 0.07 are minimal values, to show this some simulations were performed (Appendix A), obtaining for 3-uncorrelated items the standard deviation between 0.43 and 0.76, and as the correlation between the items increases, these standard deviation values will tend to increase. The suspicion is that the standard deviation values presented in the article are the standard errors obtained in the confirmatory factor analysis. This highlight is important because it justifies the non-use of these standard deviations in the reanalysis that will be made in section 3.

Table 1
Descriptive statistics, scales, and internal consistency (n = 105)

Scale	M	SD	Cronbach's alpha	# items
Sharing	1.829	0.055	0.812	3
Co-construction	2.184	0.095	0.797	3
Constructive conflict	2.279	0.071	0.875	3
Task learning	2.005	0.045	0.908	4
Reflexivity (process)	2.857	0.141	0.860	3
Reflexivity (task)	2.443	0.831	0.852	4
Boundary crossing	2.384	0.200	0.790	3
Error communication	2.124	0.122	0.905	4
Team effectiveness	2.019	0.105	0.830	3
Employee satisfaction	2.357	0.410	0.827	3
Client satisfaction	2.114	0.768	0.766	2

Source: Tan et al. (2023, p.15).

(ii) No test was presented to evaluate discriminant validity, although the highest correlation in Table 2 is equal to 0.807, which suggests that there is discriminant validity, considering the limit of 0.90 recommended by Hair Jr. et al. (2022).

Table 2
Correlation analysis of team learning behavior and team performance variables

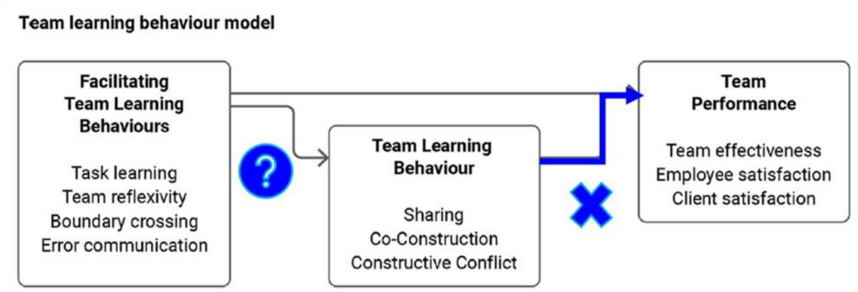
#	Scale	1	2	3	4	5	6	7	8	9	10	11
1	Sharing	1										
2	Co-construction	0.552**	1									
3	Constructive conflict	0.561**	0.807**	1								
4	Task learning	0.528**	0.689**	0.763**	1							
5	Reflexivity (process)	0.454**	0.563**	0.561**	0.606**	1						
6	Reflexivity (task)	0.366**	0.492**	0.567**	0.673**	0.663*	1					
7	Boundary crossing	0.372**	0.524**	0.558**	0.516**	0.482**	0.504**	1				
8	Error communication	0.466**	0.651**	0.649**	0.753**	0.619**	0.594**	0.478**	1			
9	Team effectiveness	0.511**	0.611**	0.632**	0.653**	0.573**	0.619**	0.476**	0.719**	1		
10	Employee satisfaction	0.413**	0.543**	0.518**	0.637**	0.542**	0.612**	0.564**	0.638**	0.742**	1	
11	Client satisfaction	0.315**	0.346**	0.368**	0.372**	0.288**	0.222*	0.158	0.223*	0.351**	0.245*	1

Source: Tan et al. (2023, p.16).
Legend: Correlations in blue are greater than 0.7. * p < 0.05; ** p < 0.01.

Considering the appropriate measurement model (reliability and discriminant validity), the next step was to evaluate the structural model, which was performed using multiple linear regression instead of structural equation modeling, yielding the results presented in Figure 2. It should be noted that the relationships proposed by hypothesis H1 were not tested. The relationships proposed in hypothesis H2 were not significant. Regarding hypothesis H3, three of the five dimensions of FTBL showed significant relationships with TP. Therefore, they were selected for continuity of the research in the qualitative stage through interviews. At the same time, the other latent variables were disregarded.

Figure 2
Multivariate regression analysis between (TLB + FTLB) and TP

			Team effectiveness			Employee satisfaction			Client satisfaction		
		Scale	B	Se	t	B	Se	t	B	Se	t
Nothing significant	1	Sharing	0.163	0.098	1.667	0.057	0.111	0.511	0.134	0.133	1.008
	2	Co-construction	0.069	0.101	0.684	0.117	0.114	1.028	0.088	0.136	0.650
	3	Constructive conflict	0.070	0.107	0.655	− 0.191	0.121	− 1.576	0.115	0.145	0.795
	4	Task learning	− 0.021	0.116	− 0.185	0.220	0.131	1.684	0.282	0.159	1.778
	5	Reflexivity (process)	0.016	0.072	0.216	0.030	0.081	0.373	0.104	0.099	1.051
Qualitative Step (interviews)	6	Reflexivity (task)	0.210	0.087	2.407**	0.216	0.098	2.211*	− 0.061	0.118	− 0.520
	7	Boundary crossing	0.029	0.075	0.390	0.248	0.085	2.931**	− 0.096	0.102	− 0.942
	8	Error communication	0.358	0.090	3.979***	0.235	0.102	2.313*	− 0.184	0.122	− 1.502



Source: Elaborated by authors from Tan et al. (2023, p.17).
Legend: The question mark on the left side of the model indicates that these relationships were not evaluated, and the "X" on the right side shows that these relationships were not significant (first three rows of the table with the results of the multiple regression).

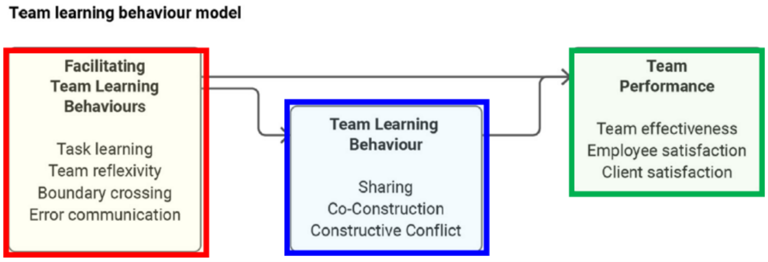
2 Rereading with the results that are available in Tan et al. (2023)

We define "**rereading**" as the reanalysis of the results that are in the article in the light of what had been proposed as objectives and hypotheses. → What did the authors not see? Or did they not comment?

Although bivariate analysis is less comprehensive than multivariate analysis, it can still provide valuable insights into the results.

The **first stage of the rereading** focused on the measurement model, i.e., only on the correlations between the dimensions of the TLB model, in Figure 3 it is observed that: (i) the five dimensions of the FTLB correlate (0.478 to 0.753, $p < 0.01$) from which it is inferred that it is plausible to propose the modeling of the FTBL as a common cause (latent second-order variable); (ii) the three dimensions of TLB correlate (0.552 to 0.807, $p < 0.01$) from which it is inferred that it is plausible to propose the modeling of TBL as a common cause (latent second-order variable); (iii) about the dimensions of TP: team effectiveness and employee satisfaction have a high correlation (0.742, $p < 0.01$), but client satisfaction has low correlations with them (0.351 and 0.245, $p < 0.05$), from which it can be inferred that there are two possibilities: analyze the three dimensions separately or group the first two in a second-order LV and keep the third isolated.

Figure 3
Correlation matrix – highlighting the correlations within the constructs



N = 105

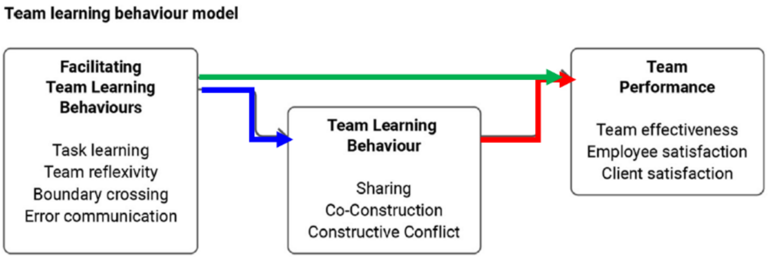
#	Scale	1	2	3	4	5	6	7	8	9	10
1	Sharing	1									
2	Co-construction	0.552*.	1								
3	Constructive conflict	0.561*.	0.807*.	1							
4	Task learning	0.528*.	0.689*.	0.763*.	1						
5	Reflexivity (process)	0.454*.	0.563*.	0.561*.	0.606*.	1					
6	Reflexivity (task)	0.366*.	0.492*.	0.567*.	0.673*.	0.663*	1				
7	Boundary crossing	0.372*.	0.524*.	0.558*.	0.516*.	0.482*.	0.504*.	1			
8	Error communication	0.466*.	0.651*.	0.649*.	0.753*.	0.619*.	0.594*.	0.478*.	1		
9	Team effectiveness	0.511*.	0.611*.	0.632*.	0.653*.	0.573*.	0.619*.	0.476*.	0.719*.	1	
10	Employee satisfaction	0.413*.	0.543*.	0.518*.	0.637*.	0.542*.	0.612*.	0.564*.	0.638*.	0.742*.	1
11	Client satisfaction	0.315*.	0.346*.	0.368*.	0.372*.	0.288*.	0.222*	0.158	0.223*	0.351*.	0.245*

Client ≠

Source: Elaborated by authors from Tan et al. (2023, p.16).
Legend: The three blocks highlighted in the correlation matrix correspond to the dimensions of the three constructs of the TLB model.

The **second stage of the rereading** focused on the structural model (Figure 4), highlighting:
H1: correlations between 0.366 and 0.763 ($p < 0.01$)
H2: correlations between 0.413 and 0.632 ($p < 0.01$) and lower for client satisfaction
H3: correlations between 0.542 and 0.719 ($p < 0.01$) and lower for client satisfaction

Figure 4
Correlation matrix – highlighting the correlations between constructs



#	Scale	1	2	3	4	5	6	7	8	9	10
1	Sharing	1									
2	Co-construction	0.552*	1								
3	Constructive conflict	0.561*	0.807*	1							
4	Task learning	0.528*	0.689*	0.763*	1						
5	Reflexivity (process)	0.454*	0.563*	0.561*	0.606*	1					
6	Reflexivity (task)	0.366*	0.492*	0.567*	0.673*	0.663*	1				
7	Boundary crossing	0.372*	0.524*	0.558*	0.516*	0.482*	0.504*	1			
8	Error communication	0.466*	0.651*	0.649*	0.753*	0.619*	0.594*	0.478*	1		
9	Team effectiveness	0.511*	0.611*	0.632*	0.653*	0.573*	0.619*	0.476*	0.719*	1	
10	Employee satisfaction	0.413*	0.543*	0.518*	0.637*	0.542*	0.612*	0.564*	0.638*	0.742*	1
11	Client satisfaction	0.315*	0.346*	0.368*	0.372*	0.288*	0.222*	0.158	0.223*	0.351*	0.245*

Client ≠ Client ≠

Source: Elaborated by authors from Tan et al. (2023, p.16).
Legend: The three blocks highlighted in the correlation matrix correspond to the hypotheses (bivariate analysis).

Considering the classification of Cohen (1988) for correlations in the behavioral sciences (0.1 small, 0.3 medium, 0.5 large), it is concluded that, from a bivariate perspective (Figure 4), all hypotheses would be confirmed. Thus, all dimensions would be investigated in the qualitative stage of Tan et al. (2023), rather than discarding six of the 11 dimensions of the model: sharing, co-construction, constructive conflict, task learning, reflexivity (process), and client satisfaction.

3 Alternative model from the correlation matrix

On the one hand, the estimation of an "**alternative model**" is recommended in the methodological literature of SEM because there are often equivalent models (with the same goodness of fit indices). On the other hand, respecifying the model can help address problems of multicollinearity or local misfit.
→ Do you have a plausible justification for respecifying the model?

Initially, we made three attempts to contact Professor Tan via email to obtain access to the original data. Still, given the lack of response, we decided to use the correlation matrix available in the article as input for modeling structural equations (Tan et al., 2023, p. 16).

Ideally, the original data should be used. In the absence of these, the best option would be to use the covariance matrix or the correlation matrix with standard deviations, allowing the software to estimate the covariances itself. However, in the present case, the standard deviations are suspected of being incorrect; hence, the decision to use what was at hand: the correlation matrix.

Cudeck (1989) explains that this situation is not ideal and that some problems may occur, such as the reproduced correlation matrix having values different from 1 on the diagonal and the standard errors having some bias compared to the estimation from the covariance matrix. In the present study, we will analyze the fully standardized solutions as recommended by Matsueda (2012) and the reproduced matrix (i.e., the fitted one).

Thus, after critical reading and rereading, we now move on to the proposal and estimation of an alternative model, which is always commented on in SEM textbooks, given the possibility of different models having the same results for the goodness of fit indices of the model, that is, equivalent models (Kline, 2023).

3.1 Alternative model: specification

In general, when using covariance-based structural equation modeling (CB-SEM), the objective is to test hypotheses about the relationships between latent variables (LVs). However, in the present case we already have some results and the model that will be presented below should not be understood as confirmatory in the sense of theory testing, because it was adjusted to the data, thus, in order to have a more robust contribution in terms of testing the TBL model, we should replicate the research in a new sample, but this is not the primary focus of this article.

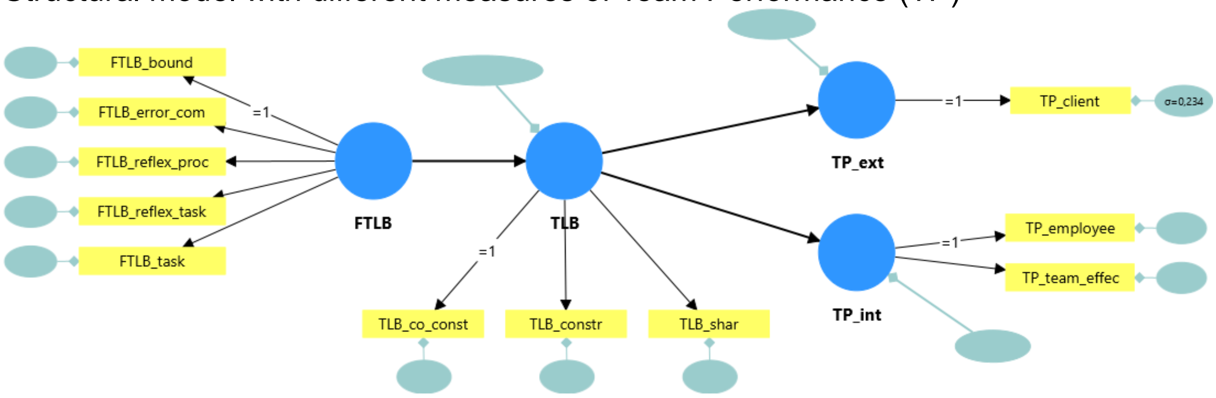
The **first adjustment** in the model involved modeling the constructs as second-order variables. On the data side, this was possible because the dimensions presented high correlations with each other, as commented in Figure 3, except Team performance, which had a dimension with low correlations (client satisfaction) and therefore, two constructs for TP were used in the model of Figure 5, one with an external focus (customer) and the other with an internal focus (employee and team). On the method side, the decision to use first-order LVs as indicators of second-order LVs is known as the "two-stage approach" (Hair Jr. et al., 2024) and is based on the logic of item parcels (Little et al., 2022).

The **second adjustment** was the removal of the direct relationship between FLB and TP, because with the three relationships, the structural coefficients gave very incoherent results (non-significant, negative, or with a standardized value higher than 1.0), which are indicative of excessive collinearity (Cohen et al., 2003).

Moreover, finally, the **third adjustment** was the specification of the error term for the TP construct as measured by a single indicator (client satisfaction). This calculation was made according to Kline (2023, pp. 275, 279) as follows:

1. Variance of the error term = $(1 - r_{xx}) \cdot s_{x_i}^2 = (1 - 0.766) \cdot 1 = 0.234$
2. $r_{xx} = 0.766$ (Cronbach’s alpha on Table 1)
3. $s_{x_i}^2 = 1$ (correlation matrix)

Figure 5
Structural model with different measures of Team Performance (TP)



Source: Elaborated by authors from Tan et al. (2023, p.5).
Legend: FTBL = Facilitating Team Learning Behaviors: Task learning, team learning, Boundary crossing, Error communication;
TBL = Team learning behavior: Sharing, Co-construction, Constructive conflict;
TP = Team performance: Team effectiveness, Employee satisfaction, Client satisfaction.
The blue balls represent second-order LV, and the yellow rectangles represent first-order LV, which were measured in the article by Tan et al. (2023) using 2, 3, or 4 items, as shown in Table 1.
Note: The error term of item TP_client was fixed a priori at the value 0.234

3.2 Alternative model: estimation

To estimate the model in SmartPLS 4 it is necessary to save the correlation matrix (Table 2) in an Excel file, including the following information: "cov" in the first upper-left cell, variable names in the first row and in the first column, next to the correlation matrix add three more columns #mean, #stddev and #cases, as presented in Appendix B. All means are equal to zero, and standard deviations are equal to 1 because we are using a matrix of correlations as input.

Then, simply:

1. Open SmartPLS 4
2. New Project > Assign a Name > Create
3. Import data file > select the Excel file > Open > Import
4. Back > Create model > Model type = CB-SEM > name > save
5. Make the template
6. Setting the error term > Double click > Variance = 0.234 > Apply
7. Save > Calculate > Basic CB SEM algorithm

- A detailed description is available at Hair et al. (2025).

The estimation of the model in the lavaan package of the R software followed the recommendations given in the tutorial (Rosseel, 2025). Moreover, in Kline (2023), the results obtained in SmartPLS 4 are compared and complemented. The script is available in Appendix 3 to facilitate the reproducibility of analysis and peer review (Open Science).

3.3 Alternative model: evaluation

To evaluate the measurement model, all constructs were correlated with each other (confirmatory factor analysis), and the fit of the model presented satisfactory indices like those of Tan et al. (2023): $\chi^2 = 60.86$, df = 39, $\chi^2/df = 1.56$, CFI = 0.970, RMSEA = 0.073, CI90 [0.033; 0.107], SRMR = 0.039.

The diagonal of the residual matrix contained only values equal to zero; the distribution of these residuals was normal (visual analysis in the histogram and Shapiro test with p-value = 0.19). The highest residual was equal to 0.109, and all the others were less than 0.1.

Convergent validity and reliability were considered adequate because all constructs had an average variance extracted (AVE) greater than 0.5, as well as Cronbach's alpha and composite reliability values greater than 0.7 (Hair Jr. et al., 2022).

However, discriminant validity, according to the Fornell and Larcker criterion, was not considered adequate because there are two correlations between the LV that exceed the values of the square root of the AVE (Table 3). Another criterion used when analyzing discriminant validity with the HTMT matrix is to examine the absolute value, with a limit of 0.9 recommended by Hair Jr. et al. (2022). A third possibility is to compare the free model (CFA with all correlations being estimated) against a model in which the correlation between two LVs is fixed at 1 (restricted model) or against a model in which the two LVs are aggregated into one.

By setting the correlation between two constructs at 1, the result was the warning "covariance matrix of latent variables is not positive definite", so it was decided to aggregate the items of the two constructs with the highest correlation (FTBL and TP_int). The new model had the following results: ($\chi^2 = 74.99$, df = 42, $\chi^2/df = 1.79$, CFI = 0.955, RMSEA = 0.086, CI90 [0.054; 0.118], SRMR = 0.042). The comparison of the free model with the constrained model (increase in χ^2) resulted in a p-value = 0.0027; therefore, by this criterion, there is discriminant validity.

Table 3

Confirmatory factor analysis results

Latent variable	FTLB	TLB	TP_ext	TP_int
FTLB	**0,771**			
TLB	0,884	**0,817**		
TP_ext	0,393	0,464	**0,875**	
TP_int	0,901	0,758	0,407	**0,862**
Cronbach's alpha	0,877	0,842	1,000	0,852
Composite reliability (rho_c)	0,879	0,855	0,766	0,853
Average variance extracted (AVE)	0,595	0,668	0,766	0,743

Source: Elaborated by authors

Legend: The values in bold on the diagonal are the square root of the AVE, and the values below the diagonal are the correlations between the LV. SmartPLS 4 results are equal to lavaan.

Since lavaan offers the option to present p-values for fully standardized results, the following results are from lavaan.

The standardized factor loadings are significant ($p < 0.001$), and only two of them did not exceed 0.7, which confirms the convergent validity at the indicator level.

Table 4
Factor loadings

lhs	op	rhs	est.std	se	z	pvalue	ci.lower	ci.upper
TLB	=~	TLB_shar	0.630	0.063	9.941	0.000	0.505	0.754
TLB	=~	TLB_co_const	0.875	0.030	29.187	0.000	0.817	0.934
TLB	=~	TLB_constr	0.917	0.025	36.249	0.000	0.867	0.966
FacTLB	=~	FTLB_task	0.873	0.028	30.857	0.000	0.817	0.928
FacTLB	=~	FTLB_reflex_proc	0.733	0.049	14.945	0.000	0.637	0.829
FacTLB	=~	FTLB_reflex_task	0.756	0.046	16.497	0.000	0.666	0.845
FacTLB	=~	FTLB_bound	0.632	0.062	10.145	0.000	0.510	0.754
FacTLB	=~	FTLB_error_com	0.840	0.033	25.241	0.000	0.775	0.905
TP_ext	=~	TP_client	0.875	0.018	47.438	0.000	0.839	0.911
TP_client	~~	TP_client	0.234	0.032	7.246	0.000	0.171	0.297
TP_int	=~	TP_team_effec	0.888	0.033	26.620	0.000	0.822	0.953
TP_int	=~	TP_employee	0.836	0.038	21.809	0.000	0.761	0.911

Source: Elaborated by authors
Legend: est.std = standardized factorial loading.

Next, the structural model was estimated (Figure 5), obtaining the following goodness of fit of the model: $\chi^2 = 83.00$, df = 41, p-value < 0.001, χ^2/df = 2.02, CFI = 0.943, RMSEA = 0.099, CI90 [0.068; 0.129], SRMR = 0.054).

All structural coefficients (direct effects) were significant ($p < 0.001$), with very high R^2 values. Cohen (1998) classifies a value of R^2 equal to 25% as large for the behavioral sciences. That is, values of R^2 equal to or greater than 70% are not expected, as observed in Table 5.

Table 5
Standardized path coefficients and indirect effects

Structural relations	label	Std.all	Std.Err	z-value	P(>|z|)	R^2
TLB ~ FacTLB	(b1)	0.935	0.026	35.446	0.000	0.875
TP_ext ~TLB	(b2)	0.461	0.096	4.792	0.000	0.213
TP_int ~TLB	(b3)	0.836	0.045	18.643	0.000	0.699
indirect_effect (FTLB --> TLB --> TP_ext)	b1*b2	0.432	0.092	4.707	0.000	
indirect_effect (FTLB --> TLB --> TP_int)	b1*b3	0.782	0.049	16.024	0.000	

Source: Elaborated by authors

Although the items used to measure the constructs possess content validity (as noted in Tan et al., 2023, p. 24), the participants' responses to the different constructs were very similar, raising questions about discriminant validity, as discussed in Table 3, and the high values of R^2. This type of result raises the suspicion of common method bias

(Podsakoff et al., 2012). However, there is no effective method to solve this problem a posteriori.

4 Discussion and Conclusion

The possibility of reanalyzing structural equation models based on summary measures, such as a covariance matrix, a correlation matrix with standard deviations, is widely disseminated in SEM textbooks. This year (2025), it became even more publicized due to the new version of the SmartPLS 4 software, which incorporated the maximum likelihood algorithm to estimate SEM based on covariances. When installing SmartPLS 4, 17 examples are available, and the article by Hair Jr. et al. (2025) provides detailed examples of the software's use.

Despite this ease and the expectation that having access to data, we could apply new methods to old data, – as was done by Levitt and List (2011) When they reanalyzed Hawthorne's data and disconfirmed the results that we have been repeating for decades – it has not been common to find articles in this style, so we decided to focus more on the methodological contribution, seeking to highlight the importance of **critical reading**, **method-based rereading**, and **reanalysis** of the data, even when the original data are not available.

The short answer to the question posed in the article's title is yes. The longer answer is that SEM is not just a statistical method for analyzing structures of covariance. It is also a way of thinking about research, involving theory-building that deals with abstract concepts and imagining ways to operationalize these constructs in a manner that makes empirical research possible. In this sense, we can compare SEM with mind maps, concept maps, and other ways of representing constructs and relationships.

Even when one does not intend to apply SEM, the potential gain from the critical reading and the rereading grounded in the method can lead readers to a depth of understanding that is not possible with floating reading or with the abstracts generated by artificial intelligence (at least for now). We hope that this article raises awareness of these points and serves as a tutorial for beginners.

Regarding the article by Professor Tan et al., we can highlight the following: Firstly, they should not have discarded any dimension in the qualitative stage. Secondly, all facilitators promote Team Learning Behavior, which, in turn, enhances team performance. For future studies that use these scales, we recommend taking some a priori measures to minimize common method bias.

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Appendix A – Simulation 1 and 3 non-correlated items (5-point Likert)

1 item - Likert 5 points
Uniform

simulation		actual
value	%	
1	20%	23%
2	20%	20%
3	20%	21%
4	20%	20%
5	20%	16%
	100%	100%
	mean =	**2,87**
	s.d. =	**1,40**

1 item - Likert 5 points
Assymetrical

simulation		actual
value	%	
1	5%	2%
2	10%	7%
3	15%	16%
4	20%	15%
5	50%	60%
	100%	100%
	mean =	**4,25**
	s.d. =	**1,07**

1 item - Likert 5 points
Very asymmetrical

simulation		actual
value	%	
1	0%	0%
2	0%	0%
3	10%	11%
4	30%	33%
5	60%	55%
	100%	100%
	mean =	**4,44**
	s.d. =	**0,69**

3 item - Likert 5 points
Uniform

simulation		actual
value	%	
1	20%	20%
2	20%	25%
3	20%	19%
4	20%	18%
5	20%	17%
	100%	100%
	mean =	**2,89**
	s.d. =	**0,76**

3 item - Likert 5 points
Assymetrical

simulation		actual
value	%	
1	5%	5%
2	10%	9%
3	15%	16%
4	20%	22%
5	50%	49%
	100%	100%
	mean =	**4,01**
	s.d. =	**0,72**

3 item - Likert 5 points
Very asymmetrical

simulation		actual
value	%	
1	0%	0%
2	0%	0%
3	10%	13%
4	30%	33%
5	60%	54%
	100%	100%
	mean =	**4,41**
	s.d. =	**0,43**

$Var(aX) = a^2 \cdot Var(X)$

Independent variables: $Var(X_1 + X_2 + X_3) = Var(X_1) + Var(X_2) + Var(X_3)$

$$Var\left(\frac{X_1 + X_2 + X_3}{3}\right) = \frac{\mathbf{1}}{\mathbf{9}} \cdot [Var(X_1) + Var(X_2) + Var(X_3)]$$

More items, lower standard deviation → central theorem limit!

Appendix B – Correlation Matrix for Import into SmartPLS 4

Formatting in Excel = lower matrix

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
1	cov	TLB_shar	TLB_co_const	TLB_constr	FTLB_task	FTLB_reflex_proc	FTLB_reflex_task	FTLB_bound	FTLB_error_com	TP_team_effec	TP_employee	TP_client	#mean	#stddev	#cases
2	TLB_shar	1											0	1	105
3	TLB_co_const	0,552	1										0	1	105
4	TLB_constr	0,561	0,807	1									0	1	105
5	FTLB_task	0,528	0,689	0,763	1								0	1	105
6	FTLB_reflex_proc	0,454	0,563	0,561	0,606	1							0	1	105
7	FTLB_reflex_task	0,366	0,492	0,567	0,673	0,663	1						0	1	105
8	FTLB_bound	0,372	0,524	0,558	0,516	0,482	0,504	1					0	1	105
9	FTLB_error_com	0,466	0,651	0,649	0,753	0,619	0,594	0,478	1				0	1	105
10	TP_team_effec	0,511	0,611	0,632	0,653	0,573	0,619	0,476	0,719	1			0	1	105
11	TP_employee	0,413	0,543	0,518	0,637	0,542	0,612	0,564	0,638	0,742	1		0	1	105
12	TP_client	0,315	0,346	0,368	0,372	0,288	0,222	0,158	0,223	0,351	0,245	1	0	1	105

After importing into SmartPLS 4 = full matrix

Raw data (first 100 of 105 lines)

cov	TLB_shar	TLB_co_const	TLB_constr	FTLB_task	FTLB_reflex_proc	FTLB_reflex_task	FTLB_bound	FTLB_error_com	TP_team_effec	TP_employee	TP_client	#mean	#stddev	#cases
TLB_shar	1,000	0,552	0,561	0,528	0,454	0,366	0,372	0,466	0,511	0,413	0,315	0,000	1,000	105,000
TLB_co_const	0,552	1,000	0,807	0,689	0,563	0,492	0,524	0,651	0,611	0,543	0,346	0,000	1,000	105,000
TLB_constr	0,561	0,807	1,000	0,763	0,561	0,567	0,558	0,649	0,632	0,518	0,368	0,000	1,000	105,000
FTLB_task	0,528	0,689	0,763	1,000	0,606	0,673	0,516	0,753	0,653	0,637	0,372	0,000	1,000	105,000
FTLB_reflex_proc	0,454	0,563	0,561	0,606	1,000	0,663	0,482	0,619	0,573	0,542	0,288	0,000	1,000	105,000
FTLB_reflex_task	0,366	0,492	0,567	0,673	0,663	1,000	0,504	0,594	0,619	0,612	0,222	0,000	1,000	105,000
FTLB_bound	0,372	0,524	0,558	0,516	0,482	0,504	1,000	0,478	0,476	0,564	0,158	0,000	1,000	105,000
FTLB_error_com	0,466	0,651	0,649	0,753	0,619	0,594	0,478	1,000	0,719	0,638	0,223	0,000	1,000	105,000
TP_team_effec	0,511	0,611	0,632	0,653	0,573	0,619	0,476	0,719	1,000	0,742	0,351	0,000	1,000	105,000
TP_employee	0,413	0,543	0,518	0,637	0,542	0,612	0,564	0,638	0,742	1,000	0,245	0,000	1,000	105,000
TP_client	0,315	0,346	0,368	0,372	0,288	0,222	0,158	0,223	0,351	0,245	1,000	0,000	1,000	105,000

Appendix 3 – Lavaan script with all analysis

```
# Correlations from https://doi.org/10.1016/j.destud.2023.101190

library(lavaan)
library(semTools)

# [step 1] input of correlations (n = 105 cases --> "n" in the step 3)

lower <- '
1
0.552 1
0.561 0.807 1
0.528 0.689 0.763 1
0.454 0.563 0.561 0.606 1
0.366 0.492 0.567 0.673 0.663 1
0.372 0.524 0.558 0.516 0.482 0.504 1
0.466 0.651 0.649 0.753 0.619 0.594 0.478 1
0.511 0.611 0.632 0.653 0.573 0.619 0.476 0.719 1
0.413 0.543 0.518 0.637 0.542 0.612 0.564 0.638 0.742 1
0.315 0.346 0.368 0.372 0.288 0.222 0.158 0.223 0.351 0.245 1
'

matriz.cor <- getCov(lower)
colnames(matriz.cor)     <-     rownames(matriz.cor)     <-     c("TLB_shar",
"TLB_co_const",      "TLB_constr",      "FTLB_task",      "FTLB_reflex_proc",
"FTLB_reflex_task",     "FTLB_bound",     "FTLB_error_com",     "TP_team_effec",
"TP_employee", "TP_client")
matriz.cor

###############
## 1 - CFA free
###############

# [step 2] model specification
modelo.1 <- '
```

```
# measurement model
TLB =~ TLB_shar + TLB_co_const + TLB_constr
FacTLB =~ FTLB_task + FTLB_reflex_proc + FTLB_reflex_task + FTLB_bound +
FTLB_error_com
TP_ext =~ TP_client
TP_client ~~ 0.234*TP_client
TP_int =~ TP_team_effec + TP_employee
'

# [step 3] model estimation
modelo.1.fit  <-  cfa(modelo.1,  sample.cov=matriz.cor,  sample.nobs=105,
sample.cov.rescale = FALSE, std.lv = TRUE)

## (sample.cov.rescale=FALSE) for lavaan not to multiply by (N-1)/N, which
results in a diagonal different of 1

# [step 4] results
summary(modelo.1.fit, fit.measures=TRUE, rsquare=TRUE, standardized=TRUE)
fitMeasures(modelo.1.fit)
standardizedSolution(modelo.1.fit) # p-value for standardized results

fitted(modelo.1.fit)
residuals(modelo.1.fit)
hist(residuals(modelo.1.fit, type = "standardized")$cov)
shapiro.test(residuals(modelo.1.fit, type = "standardized")$cov)

lavInspect(modelo.1.fit,"cor.lv")
reliability(modelo.1.fit)

######################################
## 2 - CFA grouping FacTLB and TP_int
######################################

# [step 2] model specification
modelo.2 <- '
# measurement model
TLB =~ TLB_shar + TLB_co_const + TLB_constr

TP_ext =~ TP_client
TP_client ~~ 0.234*TP_client

# grouping FacTLB and TP_int
FacTLB_TPint =~ FTLB_task + FTLB_reflex_proc + FTLB_reflex_task + FTLB_bound
+ FTLB_error_com + TP_team_effec + TP_employee
'

# [step 3] model estimation
modelo.2.fit  <-  cfa(modelo.2,  sample.cov=matriz.cor,  sample.nobs=105,
sample.cov.rescale = FALSE, std.lv = TRUE)

# [step 4] apresentar os resultados
summary(modelo.2.fit, fit.measures=TRUE, rsquare=TRUE, standardized=TRUE)
fitMeasures(modelo.2.fit)
standardizedSolution(modelo.2.fit) # p-value for standardized results

anova(modelo.1.fit, modelo.2.fit) ## result --> p-value = 0.0027


######################################
## 3 - Structural model
######################################
```

```
# [step 2] model specification
modelo.3 <- '
# measurement model
TLB =~ TLB_shar + TLB_co_const + TLB_constr
FacTLB =~ FTLB_task + FTLB_reflex_proc + FTLB_reflex_task + FTLB_bound +
FTLB_error_com
TP_ext =~ TP_client
TP_client ~~ 0.234*TP_client
TP_int =~ TP_team_effec + TP_employee

# structural model
TLB ~ b1*FacTLB
TP_ext ~ b2*TLB
TP_int ~ b3*TLB

indirect_effect_EXT := b1*b2
indirect_effect_INT := b1*b3
'

# [step 3] model estimation
modelo.3.fit <- sem(modelo.3, sample.cov=matriz.cor, sample.nobs=105,
sample.cov.rescale = FALSE, std.lv = TRUE)

# [step 4] results
summary(modelo.3.fit, fit.measures=TRUE, rsquare=TRUE, standardized=TRUE)
fitMeasures(modelo.3.fit)
standardizedSolution(modelo.3.fit) # p-value for standardized results

fitted(modelo.3.fit)
residuals(modelo.3.fit)
hist(residuals(modelo.3.fit, type = "standardized")$cov)
shapiro.test(residuals(modelo.1.fit, type = "standardized")$cov)

lavInspect(modelo.3.fit,"cor.lv")
```