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Thinking Outside the Box

Structural Equation Modeling: Is it Still Worth Learning?

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ABSTRACT

Objective: this article aims to exemplify critical reading, rereading, and estimation of an alternative model using the summary data and covariance-based structural equation modeling (CB-SEM). **Methods:** we selected an article from a highly ranked journal that confirmed the importance of three out of eight antecedents of team performance. We then reanalyzed the article in three steps. **Results:** in step 1, we identified relationships that were not tested, or that were not significant, possibly due to multicollinearity (VIF > 3). In step 2, the correlation matrix indicated a discriminant validity issue and values that should have confirmed all hypotheses. In step 3, an alternative model was tested using CB-SEM and confirmed all hypotheses, with one of them as an indirect effect. **Conclusions:** structural equation modeling (SEM) is not just a statistical method for analyzing covariance structures. It is also a way of thinking about research and theory-building that involves abstract concepts and the imagination of ways to operationalize these constructs so that empirical research becomes possible.

Data Availability: Bido, Diógenes; Souza, Cesar Alexandre (2026), "Data for: "Structural Equation Modeling: Is it Still Worth Learning?" published by BAR - Brazilian Administration Review", Mendeley Data, V1, doi: http://doi.org/10.17632/r29gd4tv33.1. BAR – Brazilian Administration Review encourages data sharing but, in compliance with ethical principles, it does not demand the disclosure of any means of identifying research subjects.

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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. 5)

Although structural equation modeling (SEM) has a long history and is widely used across various areas of Applied Social Sciences, it remains a challenging topic for students and new researchers, as learning it requires significant effort, especially when one has little experience with quantitative methods in general.

The lack of knowledge about SEM may lead researchers to avoid research questions that require it, or even worse, prevent them from formulating such questions. Despite this difficulty, the tools for estimating such models are increasingly more user-friendly, which can lead researchers to use them even when they do not fully master the method, resulting in questionable results.

Even if the researcher does not intend to use this method, they are likely to have to read, study, or review articles that employ 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 critical reading, rereading, and estimation of an alternative model using the summary data and covariance-based structural equation modeling.

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 conduct a critical reading by comparing the hypotheses with the methods used, the results obtained, and by highlighting any weaknesses. Second, we reread the article, considering the available results. Third, we will retest the hypotheses using the correlation matrix provided in the article and estimate the measurement and structural models through covariance-based structural equation modeling (CB-SEM). This will be done using SmartPLS 4 with the new maximum likelihood option and the lavaan package in R.

This article serves as a tutorial on interpreting CB-SEM articles and re-estimating the model, including alternative models, from the covariance or correlation matrix. Although the focus of this article is on the method itself, the discussion of the alternative model also sheds light on the phenomenon of Team Learning Behavior (TLB).

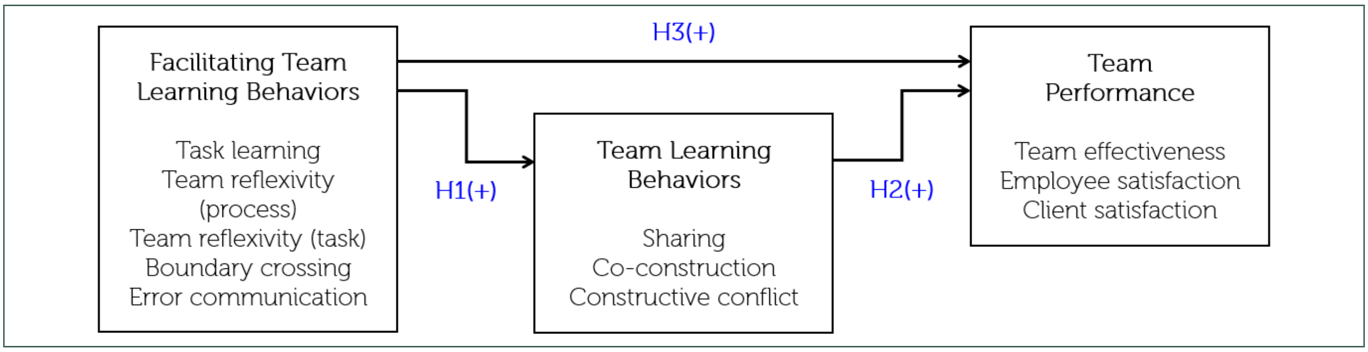
EXAMPLE SELECTION AND PRESENTATION

We selected the article by Tan et al. (2023) as a key reference for a class in a master's and doctoral course in Business Administration because it met two criteria: (1) it addresses team learning behaviors and (2) the journal is highly reputable (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 the class discussion of the article, we observed some inconsistencies (presented in the next section), which motivated the preparation of this article.

Team learning behavior: The model of Tan et al. (2023)

The model is composed of three multidimensional constructs, which are related as shown in Figure 1: (1) Facilitating Team Learning Behaviors (FTLB): Task learning, Team reflexivity, Boundary crossing, Error communication; (2) Team learning behavior (TLB): Sharing, Co-construction, Constructive conflict; (3) Team performance (TP): Team effectiveness, Employee satisfaction, Client satisfaction. The definitions of the constructs and their dimensions are available in Tan et al. (2023) and have not been repeated here for the sake of space.

Tan et al.'s (2023) research consisted of both quantitative and qualitative stages, including interviews. In this study, we only discuss the first stage. To get the most out of this article, we suggest readers stop here, read pages 1 to 17 of Tan et al. (2023), 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.



Source: Adapted from Tan, L., Kocsis, A., Burry, J., & Kyndt, E. (2023). Performance of architectural teams: The role of team learning, reflexivity, boundary crossing and error communication. *Design Studies, 87*, 101190. Copyright © 2023 Elsevier. Adapted and reproduced with permission. Note: H1(+), H2(+) and H3(+) have been added.

Figure 1. Team learning behavior model.

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

The results of Tan et al. (2023): Critical reading

We define 'critical reading' as the process of thoroughly understanding the objectives, hypotheses, methods, and results achieved, and identifying potential problems. In this sense, this step aims to address questions such as: "Are the methods chosen the appropriate ones?", "Were they used correctly?"

In the article under analysis, data were collected via a survey, yielding 105 valid responses from Australian architects who had worked in teams (two or more individuals) for at least 2 years. Confirmatory factor analysis was used to evaluate and refine the measurement model for the 11 dimensions (first-order latent variables): 5 FTLB, 3 TLB, and 3 PT, ensuring that all latent variables (LVs) had Cronbach's alpha values greater than 0.75 (Table 1).

At this stage of the analysis, there are two criticisms: (1) the standard deviation values presented in Table 1 do not seem correct because 0.04, 0.05, or 0.07 are very small values (far below the usual). To show this, we performed simulations (Appendix A), obtaining standard deviations between 0.43 and 0.76 for 3 uncorrelated items; as the correlation between the items increases, these standard deviations tend to increase. The suspicion is that the standard deviation values reported in the article are the standard errors from the confirmatory factor analysis. This highlight is important because it justifies the non-use of these standard deviations in the reanalysis of the alternative model; (2) No test was presented to evaluate discriminant validity.

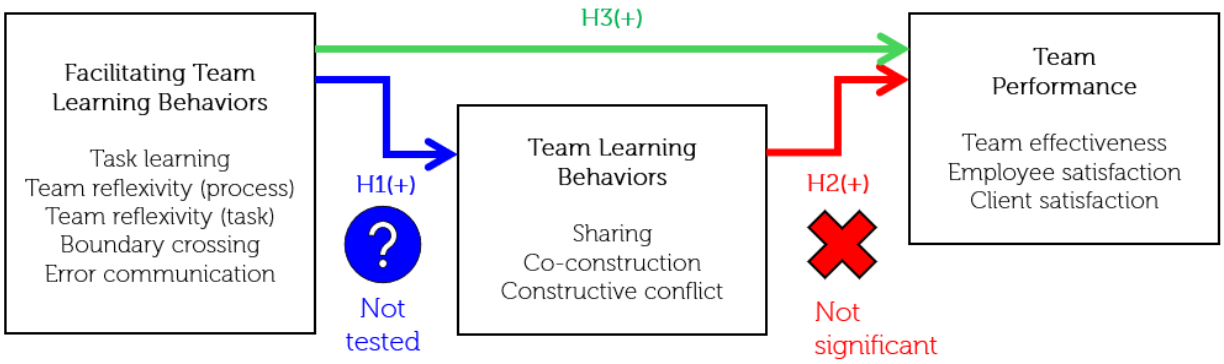
Table 1. Correlations, descriptive statistics, and internal consistency (n = 105).

First-order latent variables											
Variable	1	2	3	4	5	6	7	8	9	10	11
1 - TLB - sharing	**0.812**										
2 - TLB - co-construction	0.552	**0.797**									
3 - TLB - constructive conflict	0.561	0.807	**0.875**								
4 - FTLB - task learning	0.528	0.689	0.763	**0.908**							
5 - FTLB - team reflexivity (process)	0.454	0.563	0.561	0.606	**0.860**						
6 - FTLB - team reflexivity (task)	0.366	0.492	0.567	0.673	0.663	**0.852**					
7 - FTLB - boundary crossing	0.372	0.524	0.558	0.516	0.482	0.504	**0.790**				
8 - FTLB - error communication	0.466	0.651	0.649	0.753	0.619	0.594	0.478	**0.905**			
9 - TP - team effectiveness	0.511	0.611	0.632	0.653	0.573	0.619	0.476	0.719	**0.830**		
10 - TP - employee satisfaction	0.413	0.543	0.518	0.637	0.542	0.612	0.564	0.638	0.742	**0.827**	
11 - TP - client satisfaction	0.315	0.346	0.368	0.372	0.288	0.222	0.158	0.223	0.351	0.245	**0.766**
Mean	1.829	2.184	2.279	2.005	2.857	2.443	2.384	2.124	2.019	2.357	2.114
Standard deviation	0.055	0.095	0.071	0.045	0.141	0.831	0.200	0.122	0.105	0.410	0.768
#items	3	3	3	4	3	4	3	4	3	3	2

Note. Adapted from Tan, L., Kocsis, A., Burry, J., & Kyndt, E. (2023). Performance of architectural teams: The role of team learning, reflexivity, boundary crossing and error communication. *Design Studies, 87*, 101190. Copyright © 2023 Elsevier. Adapted and reproduced with permission. The values on the diagonal are Cronbach's alphas, and the other values are correlations. The correlation in blue is greater than the diagonal value, indicating a violation of the discriminant validity. TLB: Team Learning Behavior. FTLB: Facilitating TLB. TP: Team performance. $r \geq 0.288$ ($p < 0.01$), $0.222 \leq r \leq 0.245$ ($p < 0.05$).

Using the available information, discriminant validity can be assessed by comparing Cronbach's alphas (values on the diagonal) with the correlations (values off the diagonal) (Gaski & Nevin, 1985; Nunnally & Bernstein, 1994). Only the correlation of 0.807 exceeds the diagonal value, which is a problem because both variables were used as predictors of team performance by Tan et al. (2023) (Figure 2).

The next step was to evaluate the structural model, which was conducted using multiple linear regression rather than structural equation modeling, yielding the results presented in Figure 2. It should be noted that the relationships proposed by hypothesis H1 were not tested by Tan et al. (2023). The relationships proposed in H2 were not significant. Regarding H3, three of the five FTLB dimensions showed significant relationships with TP. Therefore, Tan et al. (2023) selected them for continuity of the research in the qualitative stage through interviews. At the same time, the other five latent variables were disregarded: TLB (sharing, co-construction, constructive conflict), FTLB (task learning, team reflexivity-process).



	9 - TP - team effectiveness		10 - TP - employee satisfaction		11 - TP - client satisfaction	
	B	t	B	t	B	t
1 - TLB - sharing	0.163	1.67	0.057	0.51	0.134	1.01
2 - TLB - co-construction	0.069	0.68	0.117	1.03	0.088	0.65
3 - TLB - constructive conflict	0.070	0.66	-0.191	-1.58	0.115	0.80
4 - FTLB - task learning	-0.021	-0.19	0.220	1.68	0.282	1.78
5 - FTLB - team reflexivity (process)	0.016	0.22	0.030	0.37	0.104	1.05
6 - FTLB - team reflexivity (task)	0.210	**2.41****	0.216	**2.21***	-0.061	-0.52
7 - FTLB - boundary crossing	0.029	0.39	0.248	**2.93****	-0.096	-0.94
8 - FTLB - error communication	0.358	**3.98*****	0.235	**2.31***	-0.184	-1.50

Source: Adapted from Tan, L., Kocsis, A., Burry, J., & Kyndt, E. (2023). Performance of architectural teams: The role of team learning, reflexivity, boundary crossing and error communication. *Design Studies, 87*, 101190. Copyright © 2023 Elsevier. Adapted and reproduced with permission. 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). Note. We calculate VIF values using the correlations shown in Table 1 and the R script provided in Appendix C.

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

To conclude this section, we can highlight some limitations observed in the analyses conducted by Tan et al. (2023).

- The discriminant validity was not assessed.
- Multiple linear regression based on summed scales does not account for measurement errors, which weakens the structural relationships.
- The relationships between FTLB and TLB were not tested.
- Dimensions of the same construct were used as predictors, resulting in multicollinearity (three VIF values greater than 3 in Figure 2) and non-significant regression coefficients (Cohen et al., 2003, Hair et al., 2024).

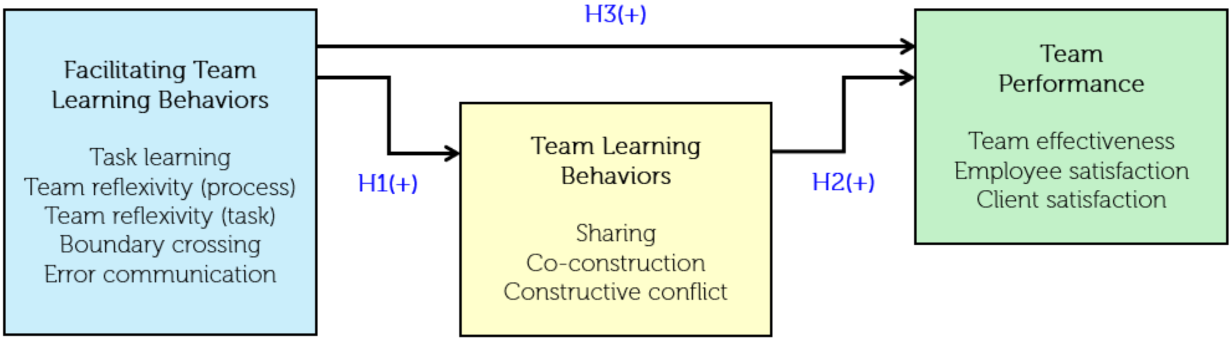
In the next section, we will address some of these weaknesses using the results from Tan et al.'s (2023) own article.

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. This step addresses questions such as "What did the authors not see?" or "What did they not comment?"

In this section, we examine evidence for the measurement of the constructs and the relationships between them (hypotheses) based on the correlation matrix (Figure 1). Although bivariate analysis is less comprehensive than multivariate analysis, it can provide valuable insights.

The first stage of the rereading focused on the measurement model, that is, only on the correlations between the dimensions of the TLB model, in Figure 3 it is observed that: (1) 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 FTLB as a common cause (second-order latent variable); (2) 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 TLB as a common cause (second-order latent variable); (3) 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, as will be shown in the next sections.



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Source: Adapted from Tan, L., Kocsis, A., Burry, J., & Kyndt, E. (2023). Performance of architectural teams: The role of team learning, reflexivity, boundary crossing and error communication. *Design Studies, 87*, 101190. Copyright © 2023 Elsevier. Adapted and reproduced with permission. Legend: The three blocks highlighted in the correlation matrix correspond to the dimensions of the three constructs of the TLB model.

Figure 3. Correlation matrix – highlighting the correlations within the constructs.

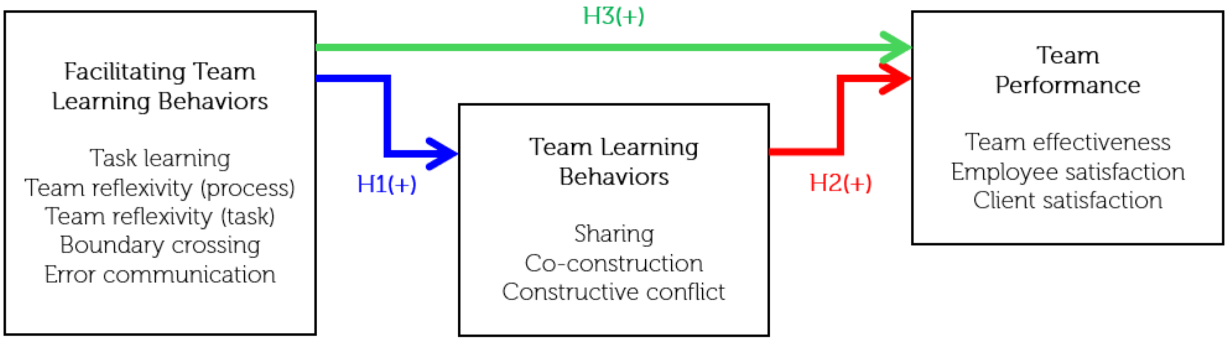
The second stage of the rereading focused on the structural model (Figure 4), highlighting:

H1: correlations from 0.366 to 0.763

H2: correlations from 0.413 to 0.632 and lower for client satisfaction (0.158–0.372)

H3: Correlations from 0.542 to 0.719 and lower for client satisfaction (0.245 to 0.351)

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.



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Source: Adapted from Tan, L., Kocsis, A., Burry, J., & Kyndt, E. (2023). Performance of architectural teams: The role of team learning, reflexivity, boundary crossing and error communication. *Design Studies, 87*, 101190. Copyright © 2023 Elsevier. Adapted and reproduced with permission. Legend: The three blocks highlighted in the correlation matrix correspond to the hypotheses (bivariate analysis). The red correlations indicate that customer satisfaction will be analyzed separately from the other two dimensions of team performance. Note: $r \geq 0.288$ ($p < 0.01$), $0.222 \leq r \leq 0.245$ ($p < 0.05$).

Figure 4. Correlation matrix – highlighting the correlations between constructs.

Concluding this section, we highlight the following insights obtained from rereading using the results from Tan et al.'s (2023) own article:

- The dimensions of the same construct that have high correlations with each other can be grouped into second-order latent variables to keep the model parsimonious and minimize multicollinearity (Cohen et al., 2003).
- Based on the correlations, there is an expectation that all hypotheses will be confirmed, even if the relationships with customer satisfaction are weaker.

In the next section, we test an alternative model using the correlation matrix as input.

ALTERNATIVE MODEL FROM THE CORRELATION MATRIX

In the third step, we estimated an 'alternative model'. On the one hand, the estimation of an 'alternative model' is recommended in the SEM methodological literature because there are often equivalent models (with the same goodness-of-fit indices). However, respecifying the model can help address problems of misspecification, multicollinearity, or local misfit. In this step, it is important to consider if there is a plausible justification for respecifying the model.

Though the original dataset was unavailable, the correlation matrix, often reported in articles using SEM analyses, can serve as input for structural equation modeling, though with limitations. This is the case in the article currently being studied (Tan et al., 2023).

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. However, some insights can be provided by the analysis. 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 an important step strongly recommended 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).

Alternative model: Specification

In covariance-based structural equation modeling (CB-SEM), the objective is to test hypotheses about the relationships among latent variables (LVs). However, in the present case, since we are analyzing a previously conducted study, we already have the original results, and the model presented below should not be understood as confirmatory in the sense of theory testing, because it was adjusted to the data. Thus, to make a more robust contribution to testing the TBL model, ideally, it would be necessary to replicate the research with a new sample, but this is not the primary focus of this article.

The first adjustment in the model involved treating constructs as second-order latent variables. On the data side, this was feasible because the dimensions showed high correlations with each other, as noted in Figure 3, except for Team Performance, which had a dimension with low correlations (client satisfaction). Consequently, two constructs for TP were used in the model shown in Figure 5: one with an external focus (customer) and the other with an internal focus (employee and team). On the methodological side, the decision was made to use first-order LVs as indicators of second-order LVs, which is known as the 'two-stage approach' (Hair et al., 2024).

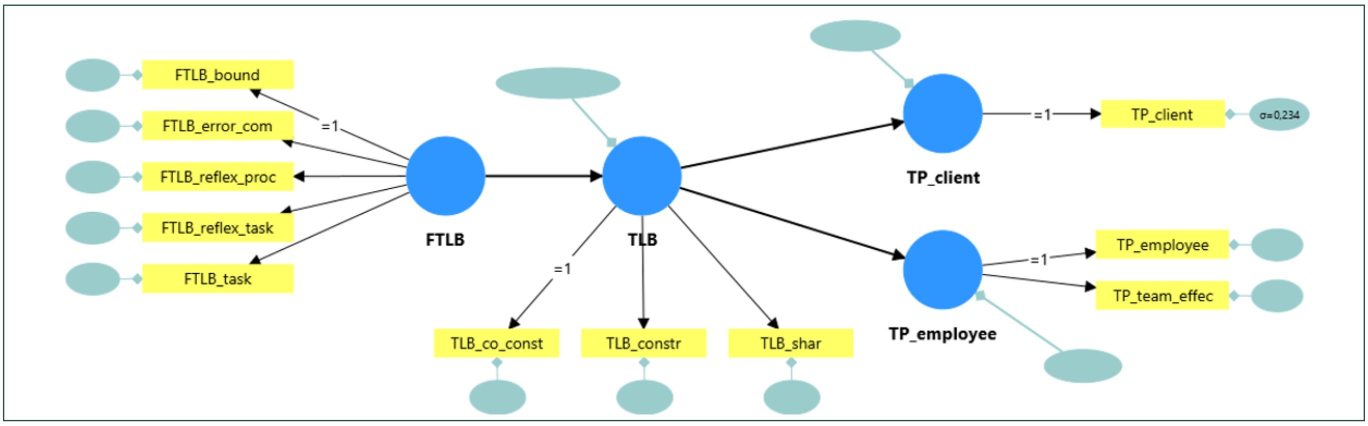
The second adjustment was the removal of the direct relationship between FTLB and TP (H3), because with the three relationships, the structural coefficients gave very incoherent results (non-significant, negative, or with a standardized value higher than 1.0), which are indicative of excessive collinearity (Cohen et al., 2003). Thus, Hypothesis H3 was tested as an indirect effect between FTLB and TP (full mediation).

Furthermore, the third adjustment involved specifying the error term for the TP construct as measured by a single indicator (client satisfaction). This calculation was performed following Kline (2023) 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, Table 1)

3. $s_{x\ i}^{2} = 1$ (correlation matrix)



Source: Elaborated by the authors based on Tan, L., Kocsis, A., Burry, J., & Kyndt, E. (2023). Performance of architectural teams: The role of team learning, reflexivity, boundary crossing and error communication. *Design Studies, 87*, 101190. Legend: FTLB = Facilitating Team Learning Behaviors: Boundary crossing, Error communication, Team reflexivity (process and task), Task learning. TLB = Team learning behavior: Sharing, Co-construction, Constructive conflict. TP_ext = Team performance (external): Client satisfaction. TP_int = Team performance (internal): Team effectiveness, Employee 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 0.234.

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

Alternative model: Estimation

To estimate the model in SmartPLS 4 it is necessary to save the correlation matrix (Table 1) 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.

A detailed description is available at Hair et al. (2025), but the main steps are:

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 model
6. Setting the error term > Double click > Variance = 0.234 > Apply
7. Save > Calculate > Basic CB - SEM algorithm

The same model was also estimated using the lavaan package in R software, following the recommendations provided in the tutorial (Rosseel, 2025). The results were then compared with those from SmartPLS 4, and the lavaan script is available in Appendix C to ensure the reproducibility of the analysis and facilitate peer review (Open Science).

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, p = 0.014, χ^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 0.109, and all 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 et al., 2022).

However, discriminant validity, according to the Fornell and Larcker criterion, was not considered adequate because two correlations between the LVs exceeded the values of the square root of the AVE (Table 2). Another method for analyzing discriminant validity involves comparing the free model (CFA with all correlations estimated) to a model where the correlation between two LVs is fixed at 1 (restricted model) or to a model where the two LVs are combined into one.

By setting the correlation between two constructs to 1, the warning 'covariance matrix of latent variables is not positive definite' appeared. Therefore, to test discriminant validity, we aggregated the two constructs with the highest correlations. (FTLB and TP_int, respectively). The new model had the following results: ($\chi^2 = 74.99$, df = 42, p = 0.001, χ^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 = 0.0027; therefore, by this criterion, there is discriminant validity.

Table 2. Confirmatory factor analysis results (Fornell & Larcker criterion).

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

Note. 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. The SmartPLS 4 results are equal to those of lavaan.

Since lavaan offers the option to present p-values for fully standardized results, the following results are from lavaan (Tables 3 and 4). All standardized factor loadings are significant (p < 0.001), and only two are below 0.7, confirming convergent validity at the indicator level.

Table 3. Factor loadings of the confirmatory factor analysis.

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

Note. Elaborated by authors. Legend: = standardized factor loading. ~~ residual variance (fixed). 1: TP_client ~~ TP_client = 0.234, that is, the residual variance is fixed a priori. 2: In confirmatory factor analysis, all constructs are correlated with each other, without the structural relations.

Next, the structural model was estimated (Figure 5), obtaining the following goodness of fit of the model: χ^2 = 83.00, df = 41, p < 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 (1988) classifies an R^2 of 25% as large in the behavioral sciences. That is, values of R^2 equal to or greater than 70% are not expected, as observed in Table 4.

Table 4. Standardized path coefficients and indirect effects.

Structural relations	label	Std.all	Std.Err	z-value	P(>|z|)	R^2
H1: TLB ~ FacTLB	(b1)	0.935	0.026	35.446	0.000	0.875
H2a: TP_ext ~ TLB	(b2)	0.461	0.096	4.792	0.000	0.213
H2b: TP_int ~ TLB	(b3)	0.836	0.045	18.643	0.000	0.699
H3a: indirect_effect (FTLB → TLB → TP_ext)	b1*b2	0.432	0.092	4.707	0.000	
H3b: indirect_effect (FTLB → TLB → TP_int)	b1*b3	0.782	0.049	16.024	0.000	

Note. Elaborated by authors. H2 and H3 were separated into (a) and (b) because the TP construct was divided into two (external and internal).

Although the items used to measure the constructs possess content validity (as noted in Tan et al., 2023, p. 24), participants' responses across the constructs were very similar, raising questions about discriminant validity (as discussed in Table 2) and the high R^2 values. This type of result raises the suspicion of a common method bias (Podsakoff et al., 2012). However, there is no effective method for solving this problem a posteriori.

In the article by Tan et al. (2023), hypothesis H3 was proposed as a direct effect (FTLB → TP), as shown in Figure 1. However, the results for this model were inconsistent (as explained in the alternative model specification). Therefore, we evaluate the relationship between these two constructs as an indirect effect fully mediated by the TLB construct: 0.461 (p < 0.001) and 0.836 (p < 0.001) for external TP and internal TP, respectively. These results are very interesting because, in this alternative model, the TLB construct plays a central role in the influence of FTLB on TP, whereas in Tan et al.'s (2023) article, the TLB construct was of no importance: (1) the relationship between FTLB → TLB was not tested, (2) the relationship between TLB → TP was not significant.

DISCUSSION AND CONCLUSION

The possibility of reanalyzing structural equation models using summary measures, such as a covariance or correlation matrix with standard deviations, is widely discussed in SEM textbooks. In 2025, it received even more attention thanks to the new SmartPLS 4 software, which added the maximum likelihood algorithm for estimating SEMs based on covariances. Seventeen examples are readily available, and the article by Hair et al. (2025) provides detailed guidance on using the software.

Despite this ease and the expectation that having access to data would allow us to apply new methods to old data, as was done by Levitt and List (2011). When they reanalyzed Hawthorne's data and disconfirmed the results we have been repeating for decades, it was uncommon to find articles in this style. Therefore, we decided to focus more on the methodological contribution, aiming to highlight the importance of critical reading, method-based rereading, and reanalysis of the data, even when the original data are unavailable.

The short answer to the question in the article's title ('Is SEM still worth learning?') is, in our view, a sound 'Yes!'. The longer answer is that SEM is not just a statistical method for analyzing covariance structure. It is also a way of thinking about research, involving theory-building that addresses abstract concepts and the imagination of ways to operationalize these constructs so that empirical research becomes possible. In this sense, we can compare SEM to mind maps, concept maps, and other methods of representing constructs and their relationships.

Even if someone does not intend to use SEM, the benefits of critical reading and rereading based on the method can help readers reach a depth of understanding that is not achievable with casual reading or AI-generated abstracts (at least for now). We hope that this article raises awareness of these points and serves as a guide for beginners.

Regarding the article by Tan et al. (2023), we can highlight the following: First, they should not have dropped any dimension during the qualitative stage, because all facilitators promote Team Learning Behavior, which, in turn, enhances team performance; in other words, all constructs are important. Second, the sample of 105 cases is small for estimating all the parameters of the full model with first-order latent variables, so using the two-stage approach (Hair et al., 2024) would be interesting because it reduces the number of parameters to be estimated and the required sample size, as we presented in Table 5. Third, potential biases from omitted variables could be minimized by including control variables such as the company's size and the team's size (Atinc et al., 2012) and the common-method bias could be addressed by incorporating an LV marker variable (Castillo et al., 2025; Chin et al., 2013).

Table 5. Sample size for model estimation using CB-SEM.

Model to be estimated	Number of LV	Number of items	Minimum sample size to detect effect	Recommended minimum sample size
Full model with all first-order LVs	11	35	195	195
Model as shown in Figure 1 [1]	3	11	119	123

Note. Prepared by the authors based on the sample size calculator by Soper (2026). 1: The final model (Figure 5) contains 4 LVs, but TP_ext has only one item, so it was not counted as a LV for the sample size estimation. 2: Values used to compute the sample size: Effect size = 0.3, Power = 0.8, alpha = 0.05

One of the intended impacts of this article is for it to be used as study material; therefore, we highlight the following limitations: (1) the article by Tan et al. (2023) is not Open Access, and perhaps an example based on an available article would have a greater impact or be easier for the reader to find, but this was the 'cost' of using a highly ranked journal article, (2) ideally, we should use a correlation matrix between the items to estimate the measurement model among the first-order latent variables. In this case, we used the correlations between the first-order latent variables, which were considered as dimensions of the second-order latent variables. The second limitation cannot be fixed, and its cause has been discussed for over a decade: "the lack of a covariance matrix or correlations and standard deviations prevents the use of these articles in future meta-analysis research or even the testing of equivalent models by other researchers." (Bido et al., 2012, p. 137). Therefore, a good practice for articles using CB-SEM is to include the item covariance matrix in the article itself, and the best practice is to keep the data open.

Finally, at the beginning of this article readers were encouraged to consult the original work by Tan et al. (2023) prior to engaging in a thorough reading of this article. If you (the reader) did so, here are some questions:

- Did you notice anything wrong or missing in Tan et al. (2023)? For example, did they not test the relationships of hypothesis H1 (FTLB → TLB)?
- Were you able to interpret the correlation matrix (Table 1) as a measurement model (Figure 3) and as a structural model (Figure 4)?

If the answer to any of these questions was no, then we probably achieved our objective.

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