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COMPARING COMPETING STRUCTURAL MODELS IN CB-SEM: AN ILLUSTRATIVE APPLICATION FOR MANAGEMENT AND BEHAVIORAL RESEARCH

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ABSTRACT

Structural equation modeling (SEM) is an advanced statistical technique used to evaluate complex relationships among latent variables. Researchers in behavioral and management sciences frequently apply structural models right after validating the measurement model, often without considering other plausible alternative (competing) models, perspectives, or explanations. Consequently, competing structural models are rarely evaluated or reported. This problem is compounded by practices such as selectively using fit indices, adopting more complex models for increased explanatory power, and relying on software-generated modification indices without a strong theoretical foundation. To improve robustness, both the hypothesized model and alternative (competing) models should be compared using fit indices and descriptive criteria for model selection, such as the Akaike Information Criterion (AIC). This paper shows how to compare a hypothesized model with competing models—both nested and non-nested—using covariance-based SEM techniques (CB-SEM; Analysis of Moment Structures [AMOS] and Linear Structural Relations [LISREL]). Nested models were compared using the $\chi 2$ difference test, while AIC was employed for non-nested models. A dataset from a published study (N=282), based on the Technology Acceptance Model, was analyzed. Results from AMOS indicated that the competing models met acceptable fit criteria just as the primary structural model did. LISREL output provided higher incremental fit indices and path coefficients than AMOS, yet both identified the same preferred model, with similar significance patterns and consistent theoretical interpretations. The study found that the initial structural model achieved better fit statistics than other competing models, whether nested or non-nested. It emphasizes the importance of model comparisons and highlights the value of testing alternative theoretical models. The paper offers a comprehensive step-by-step methodological guide for researchers to conceptualize, execute, and report these analyses. Finally, it discusses implications and recommendations for future research.

1. INTRODUCTION

Over the past twenty years, structural equation modeling (SEM) has become the preferred tool for researchers in the social, management, and behavioral sciences. Several factors explain this rising popularity. One major advantage of SEM is its ability to easily analyze both simple and complex relationships among variables, support hypothesis testing and validation, advance theory development, validate measurement instruments, and handle non-normal data (Rigdon et al., 2017; Hair et al., 2019; Zhang et al., 2020; Kline, 2023). SEM encompasses two main techniques: partial least squares structural equation modeling (PLS-SEM) and covariance-based

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structural equation modeling (CB-SEM). PLS-SEM relies on composites, or linear combinations of indicators, making it suitable for small sample sizes and complex models, with a focus on prediction (Hair et al., 2011; Hair et al., 2019). CB-SEM is based on the common factor principle, where the latent construct causes the indicators, and generally requires larger sample sizes. It is ideal for testing and confirming theories. Additionally, CB-SEM allows for testing, comparing, and interpreting competing models (Mitchell, 1992; Zhang et al., 2020; Oamen, 2024).

Both techniques (PLS-SEM and CB-SEM) consist of two main parts: the measurement (outer) model and the structural (inner) model. The measurement (outer) model assesses the reliability and validity of the relationships between latent variables and their indicators. In other words, it determines how accurately and consistently the indicators reflect the latent constructs. This relationship is evaluated using confirmatory factor analysis (CFA). The structural (inner) model examines causal relationships—such as direct, indirect, mediating, or moderating effects—among latent variables through hypothesis testing (Dash & Paul, 2021). Additionally, the structural model is typically represented as a path analysis involving latent constructs or as a comprehensive structural model illustrating the latent variables and their indicators (Collier, 2020).

Many studies have provided methodological guidelines for conducting and reporting SEM across various disciplines, including management research (Zhang et al., 2021), tourism and hospitality (Nunkoo et al., 2013; Ali et al., 2018), marketing research (Sarstedt et al., 2023), information systems (Gaskin et al., 2025), business research (Dash & Paul, 2021), and psychology (Morrison et al., 2017).

This illustrative methodology paper aims to extend the application of existing knowledge to SEM methodology by strengthening the case for testing the quality of a researcher's structural model against other plausible models derived from the same data. Given the increasing use of SEM, structural models should be tested for several reasons. For instance, some researchers misuse or misapply model fit measures by selectively using and reporting fit indices to justify or 'beautify' inherently poorly specified or 'poorly-fitting' structural models (Stone, 2021). Also, the use of empirical modification fit indices provided by SEM software to achieve or enhance acceptable model fit using correlated errors without relevant theoretical support (Weston & Gore, 2006; Hermida, 2015; Morrison et al., 2017).

Furthermore, studies by Werner & Schermelleh-Engel (2010), Akbar (2013), Chen et al. (2018), and Sarstedt et al. (2024) emphasize the importance of comparing models to justify the robustness of the theoretically developed structural model, while others consider it unnecessary after evaluating the measurement model (Gaskin et al., 2025). According to Sharma et al. (2019), Rigdon (2023), and Sarstedt et al. (2024), transparency in research is crucial for supporting robust, valid conclusions and inferences regarding researchers' choice or adoption of a specific structural model.

Similarly, comparing structural models is crucial for developing theory because it ensures the researcher considers or at least examines different potential explanations or perspectives for the phenomenon of interest (Grover et al., 2008; Roberts & Grover, 2009). In turn, this can result in better models and theories, reduce human bias toward 'preferred' models, or strengthen the existing or proposed theory by testing it against alternative (competing) models (Roberts & Grover, 2009).

Another challenge for applied researchers using SEM is balancing model parsimony with complexity. Complex models tend to overfit, resulting in better model fit indices and predictive values, such as R-squared. This may lead researchers to identify spurious path relationships that undermine parsimony, decrease generalizability, and limit the model's applicability and plausibility in other samples (Myung, 2000; Myung & Pitt, 2004; Sarstedt et al., 2024). Parsimony in SEM involves achieving a good model fit with fewer variables and paths; in other words, understanding a phenomenon of interest with fewer resources.

Typically, the structural model defined by the researcher is the primary focus of hypothesis testing in the study. In this context, Mayrhofer & Hutmacher (2020), Zitzmann & Loreth (2021), and Stone (2021) advised researchers to use multiple model fit indices and provide theoretical justifications when reporting model fit. Building on this approach, researchers should evaluate competing structural models to determine if a better, more plausible explanation of the phenomenon exists and, if so, propose a new perspective for the study (Weston & Gore, 2006; Stone, 2021). The comparison of competing models has been used to test hypotheses (Akbar, 2013; Chen et al., 2018) and as a methodological approach (Schermelleh-Engel et al., 2003; Werner & Schermelleh-Engel, 2010; Pavlov et al., 2020).

Although CB-SEM has been used to compare models since the 1980s (Anderson & Gerbing, 1988; Anderson et al., 1987; Werner & Schermelleh-Engel, 2010; Lin et al., 2017), applied

researchers in behavioral and management fields have rarely incorporated this important element into their analysis and reporting.

To close this practice gap, this paper aims to provide a clear, illustrative methodological guide for researchers in the social, behavioral, and management sciences to analyze and report competing (alternative) structural models using CB-SEM (in AMOS and LISREL).

In this illustrative methodology paper, we first introduce the main concept of SEM and provide an overview of its applications. Second, we establish the rationale for the study by discussing competing models within the framework of nested and non-nested models. Third, we outline model fit measures and the chi-square difference test methodology. Finally, we analyze and discuss the results from the dataset of the published study. We also present recommendations, future research directions, limitations, and conclusions.

2. LITERATURE REVIEW

2.1. Model Fit Measures

Commonly used fit indices include chi-square ($\chi 2$), the normed chi-square ratio ($\chi 2/df$), standardized root mean square residuals (SRMR), root mean square error of approximation (RMSEA), Comparative Fit Index (CFI), and Tucker-Lewis Index (TLI). Although the $\chi 2$ test statistic is often used as a measure of overall fit, it is frequently not considered because of its sensitivity to sample size. A model is said to fit the observed data when the model-implied covariance matrix matches the sample covariance matrix (Hu & Bentler, 1999; Schermelleh-Engel et al., 2003). Given the sensitivity of fit indices to model complexity, data quality, and sample size, Gaskin et al. (2025) and West et al. (2023) advised researchers to use a set of fit indices rather than rely on or select only one or two.

Commonly used model fit measures, as outlined by Browne & Cudeck (1993), Bentler (1992), Hu & Bentler (1999), and Byrne (2001), include $\chi 2/df$ (less than 1 to 3), SRMR (less than 0.06 to 0.08), RMSEA (less than 0.06 to 0.08) with 90% confidence intervals, TLI (greater than 0.90 to 0.95), and CFI (greater than 0.90 to 0.95).

In SEM, structural models must first be assessed for a good fit with the data. Then, models showing misfit should undergo procedures such as trimming non-significant paths, re-specifying the model, and using empirical modification indices guided by the underlying theory to make adjustments.

Therefore, establishing the fit of the structural model provides the foundation for comparing the initially developed model with other alternative (competing) models, which may be nested or non-nested.

2.1.1. Rationale and methods for comparing competing (alternative) structural equation models

According to Rigdon (2023), Rigdon et al. (2020), and Rigdon and Sarstedt (2022), SEM requires researchers to consider uncertainty beyond standard errors, including other factors within the phenomenon or the hypothesized model of interest. This obligation encourages SEM users to critique hypothesized structural models (representing the phenomenon of interest) by comparing them with other perspectives or alternative models (Sarstedt et al., 2024; Nuzzo et al., 2015). For the measurement model, comparisons can be made among competing CFA models (Oamen, 2024). However, for structural models, the basis for comparing competing or alternative models depends on whether the models are nested or non-nested (Lin et al., 2017; Pavlov et al., 2020). Gaskin et al. (2025) argued that evaluating structural model fit is unnecessary when the fit of the measurement model has been deemed adequate. They suggested that model fit is a global test that should precede hypothesis testing of structural paths. Nonetheless, this paper contends that alternative models—based on imposing constraints on selected paths supported by theory—should be compared with the initial structural model to identify the most suitable model for hypothesis testing. In accordance with the positions of Werner & Schermelleh-Engel (2010), Akbar (2013), and Chen et al. (2018), this approach tests the robustness of the initially specified model against competing specified structural models within the CB-SEM framework, using a dataset from a published study (Oamen, 2023).

A model is considered nested when its parameters (see Figure 1. Models 2, 3, 4, and 5) are a subset of those in another model (Model 1). The nested model includes all the parameters of the parent model, with at least one parameter set to zero or removed. In other words, the more restrictive models 2 to 5 (with fixed parameters and fewer degrees of freedom) are nested within a less restrictive Model 1 (with more free parameters and greater degrees of freedom). Fixed parameters refer to paths in the model that are either removed or fixed to zero.

Additionally, according to Werner & Schermelleh-Engel (2010), removing or changing a parameter in one model while keeping it in the other means that one model has an extra path, parameter, correlation, or loading that the other model lacks (which is fixed to zero). According

to Schermelleh-Engel et al. (2003), Models 2 to 5 are created from Model 1 by fixing at least one parameter to zero.

For equivalent models, such as models 4 and 6, models 1 and 7, and models 1 and 10, they share the same fit indices and correlations but differ in path configuration or relationships.

Generally, the standard way to compare Nested Models 2 to 4 with the initial (or main) Model 1 is through the chi-square ($\chi 2$) difference test. If this $\chi 2$ difference test is significant, it shows a lack of equivalence, and Model 1 is retained because the free parameters improve the fit (meaning the constrained model fits worse). However, if the test is not significant, it indicates that the fit of Models 2 to 4 is not substantially different from that of Model 1. In such cases, Models 2 to 4 are preferred for the sake of simplicity and parsimony.

Furthermore, as a general guideline for nested models (where one model is a subset of the other), differences among two or more competing models are initially assessed based on their fit and simplicity. If the differences are minor, a decision can be made using the $\chi 2$ difference test.

However, for two non-nested models, the structures differ. There are two possible scenarios: 1) Consider two models (Model 1 and Model 6 in Figure 1) with the same latent constructs X1, X2, X3, and Y. In Model 1, the path from X1 to X2 is shown, while in Model 6, it appears as a path from X3 to X2. 2) Another example involves Model 8 and Model 9, where q1 and n1 are indicators of latent variables X1 and X3, respectively. However, in Model 9, q1 and n1 indicate different latent variables, with q1 pointing to X3 and n1 to X1.

For non-nested models (Models 1 vs. 6 and Models 8 vs. 9), model comparison is based on the Akaike Information Criterion (AIC; Akaike, 1987; Lin et al., 2017). The model with the lower AIC value is preferred. The AIC metric considers both model simplicity and adequate fit among competing models.

Equivalent models were excluded from the evaluation in this study because when two competing models are structurally identical with the same model fit, there is no reason to compare them other than for theoretically justified reasons.

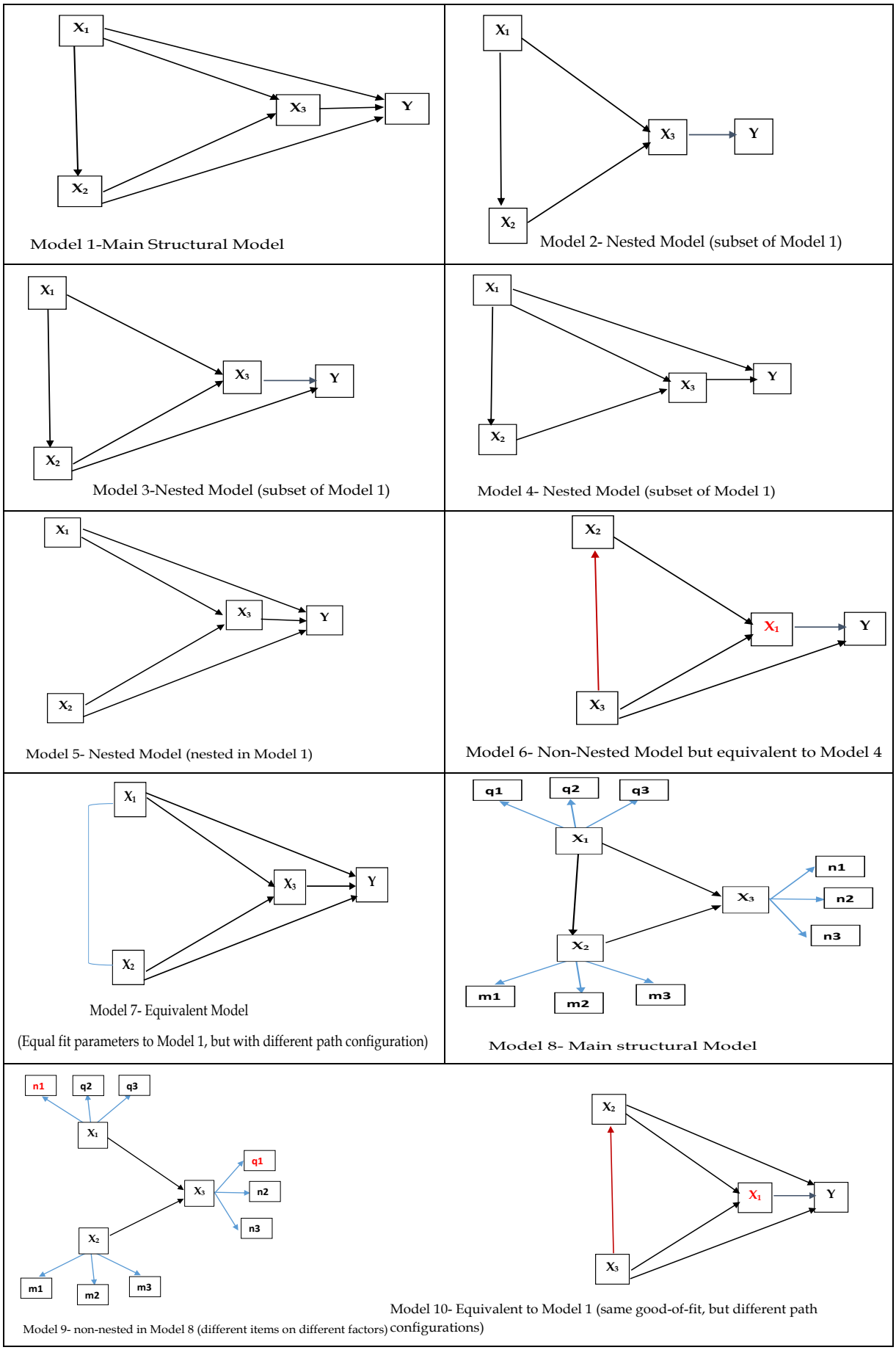

Figure 1. Examples of Nested, Non-Nested, and Equivalent Models

In this paper, alternative (competing) models were assessed using path analysis with full structural models in AMOS (Arbuckle & Wothke, 1999; Arbuckle, 2014) and LISREL (Joreskog & Sorbom, 1996; Joreskog & Sorbom, 2022). Empirical data were utilized to test this methodology. Using real empirical data is recommended because simulated data may not accurately represent reality and might overlook the human element in data analysis (Sharma et al., 2019; Pavlov et al., 2020; Sarstedt et al., 2024).

3. METHOD

The analytical illustrative study used a dataset from a published paper by Oamen (2023), which evaluated technology adoption among pharmaceutical executives (N=282; males=205, females=77) using the Technology Acceptance Model (TAM) framework (Davis, 1989; Davis & Granic, 2024). In that study (Oamen, 2023), a hypothetical model was developed with the factor-based SEM software WarpPLS (Kock, 2022). The key variables included perceived usefulness (PU), measured with 6 indicators (CR=0.938; CA=0.938; AVE=0.717), perceived ease of use (PEOU), measured with 6 indicators (CR=0.876; CA=0.867; AVE=0.515), behavioral intention (BIU), measured with 5 indicators (CR=0.907; CA=0.906; AVE=0.662), and technology impact on performance (TechIMP), measured with 9 indicators (CR=0.917; CA=0.917; AVE=0.552). The model also demonstrated adequate convergent validity, with HTMT ratios below 0.85 (Oamen, 2023). Later, the model was replicated using both AMOS and LISREL, which are CB-SEM statistical software. The methodology closely follows that of Sarstedt et al. (2024), who used CB-SEM and PLS-SEM to analyze the same data. This study employed only CB-SEM with two different software packages—AMOS and LISREL. For model estimation, the default maximum likelihood estimator in each software was used. The structural models were not subject to further fit improvement through modification indices.

3.1.Data Analysis

3.1.1. Test of normality

To evaluate the dataset's distribution, a univariate normality test was performed using skewness and kurtosis measures (acceptable ranges ±2 and ±7). Multivariate normality was examined with a test statistic outside the critical ratio ±1.96 at a significance level of 0.05 (Morrison et al., 2017; Collier, 2020).

In this study, we used the default maximum-likelihood estimator in AMOS and LISREL for model estimation, assuming data normality. The univariate normality test showed skewness

values for PU indicators ranging from -1.179 for item 2 to -1.613 for item 1; PEOU ranging from -0.337 for item 1 to -0.996 for item 4; BIU ranging from -1.455 for item 3 to -1.737 for item 5; and TechIMP ranging from -0.833 for item 3 to -1.894 for item 6. The kurtosis values are as follows: PU indicators from 1.737 for item 2 to 3.600 for item 1; PEOU from 0.096 for item 6 to -0.874 for item 1; BIU from 1.623 for item 3 to 3.996 for item 2; and TechIMP from -0.005 for item 3 to 4.045 for item 6. Therefore, the data meet the normality requirement.

Furthermore, to examine multivariate normality, a normalized multivariate kurtosis value greater than 5 indicates multivariate non-normality (Byrne, 2001). The data showed evidence of multivariate non-normality (kurtosis value = 288.24). To address concerns about multivariate normality and normalize the distribution, several strategies can be adopted. For example, bootstrapping corrects bias in standard errors and fit statistics for both CFA and structural models (Bollen & Stine, 1992). Bollen-Stine bootstrapping is used to estimate model fit parameters for non-normal data (Bollen & Stine, 1992). Another strategy is to build a CFA, identify the highest contributors to the multivariate kurtosis statistic, remove them, and re-evaluate the impact (Mardia, 1970). Researchers are encouraged to use robust maximum-likelihood estimators or bootstrapping when non-normality is present or anticipated.

3.1.2. Comparing alternative (competing) models using the chi-square (χ2) difference test

Since Models 2 to 5 are nested within Model 1, the chi-square difference test was used to compare the less restrictive Model 1 (with fewer degrees of freedom and free parameters) to the more restricted models (3 to 5), which have higher degrees of freedom and one or more parameters fixed to zero or eliminated.

The χ2 difference test measures the difference in χ2 values between two models, one nested within the other, based on the difference in degrees of freedom (df), and evaluated at the χ2 value for one degree of freedom.

The χ^2/df (chi-square difference test) is presented as:

$$\Delta\chi2\ calculated = \chi2model\ 2\ (3\ to\ 5) - \chi2model\ \ 1 \qquad (1)$$

$$\text{Diff. in df } (\Delta\text{df}) = \text{dfmodel 2 (3 to 5)} - \text{dfmodel 1} \qquad (2)$$

$$\chi2 \text{ critical at df} = 1 \text{ equals 3.84 at p} < 0.05 \qquad (3)$$

$$\Delta\chi2 \text{ calculated is greater than } X^2 \text{ critical} \qquad (4)$$

Model 2 is the more restrictive (nested) model with fewer parameters and therefore has more degrees of freedom, while Model 1 is the less restrictive model with more parameters and fewer degrees of freedom.

Equations 1 to 4 detail the process for calculating the $\chi 2$ difference test between two nested models. Equation 4 can be computed manually using a chi-square table or with online software. If the resulting $\Delta\chi 2$ exceeds the critical $\chi 2$ value, indicating a significant difference, then the original Model 1 is retained. This suggests it is reasonable and beneficial to estimate additional parameters in the larger Model 1 rather than fixing them to zero or removing them in Model 2.

However, if the difference is not significant (the calculated $\Delta\chi 2$ is less than the critical $\chi 2$), there is no added benefit from the freely estimated parameters in the larger model (Model 1). Therefore, the smaller model (Model 2) is preferred.

3.1.3. Model specification

The goal of model specification and re-specification using alternative approaches is to develop and evaluate different empirical pathways to explain a phenomenon or research interest in a theoretically sound, best-fitting, and parsimonious manner.

The main structural model, Model 1, was based on the Technology Acceptance Model (TAM), where PU (X1) and PEOU (X2) influence TechIMP (Y) both directly and indirectly through BIU (X3). PU (X1) also directly affects PEOU (X2).

In Model 2, the direct paths from PU to TechIMP and from PEOU to TechIMP were set to zero (in LISREL) or removed (in AMOS). Only the mediating relationships were kept. All other paths stayed the same.

In Model 3, the direct path from PEOU to TechIMP was set to zero (in LISREL) or eliminated (in AMOS). All other paths stayed the same.

For Model 4, the direct path from PU to TechIMP was set to zero in LISREL or removed in AMOS. All other paths remained unchanged.

Also, the non-nested Model 6 was specified with different path configurations, where PEOU (X2) and BIU (X3) influence TechIMP (Y) indirectly through PU (X1). In this model, BIU (X3) directly influences PEOU (X2). Since Model 1 and Model 6 are non-nested, AIC was used to compare them (Lin et al., 2017).

3.1.4. Analytical procedures

Generally, the illustrations for model comparison using AMOS and LISREL were conducted under equivalent analytical conditions, including the same CB-SEM framework, dataset, estimation method, model specification, and reporting structure. The alternative models (both nested and non-nested) shown in Figure 1 were estimated using AMOS and LISREL algorithm as described below.

In AMOS, the full structural model (Model 1) was developed. Then, alternative competing models were generated using the model specification search function. Models 2 to 4 were created by removing or constraining specific paths to zero, as described earlier. Note that the primary path relationships (PU to PEOU, PU to BIU, PEOU to BIU, and BIU to TechIMP) were maintained to prevent mis-specification of the alternative models. Afterward, the fit indices of the models were evaluated against the criteria. Models with acceptable fit were kept; others were discarded. The main path model is shown in Figure 2.

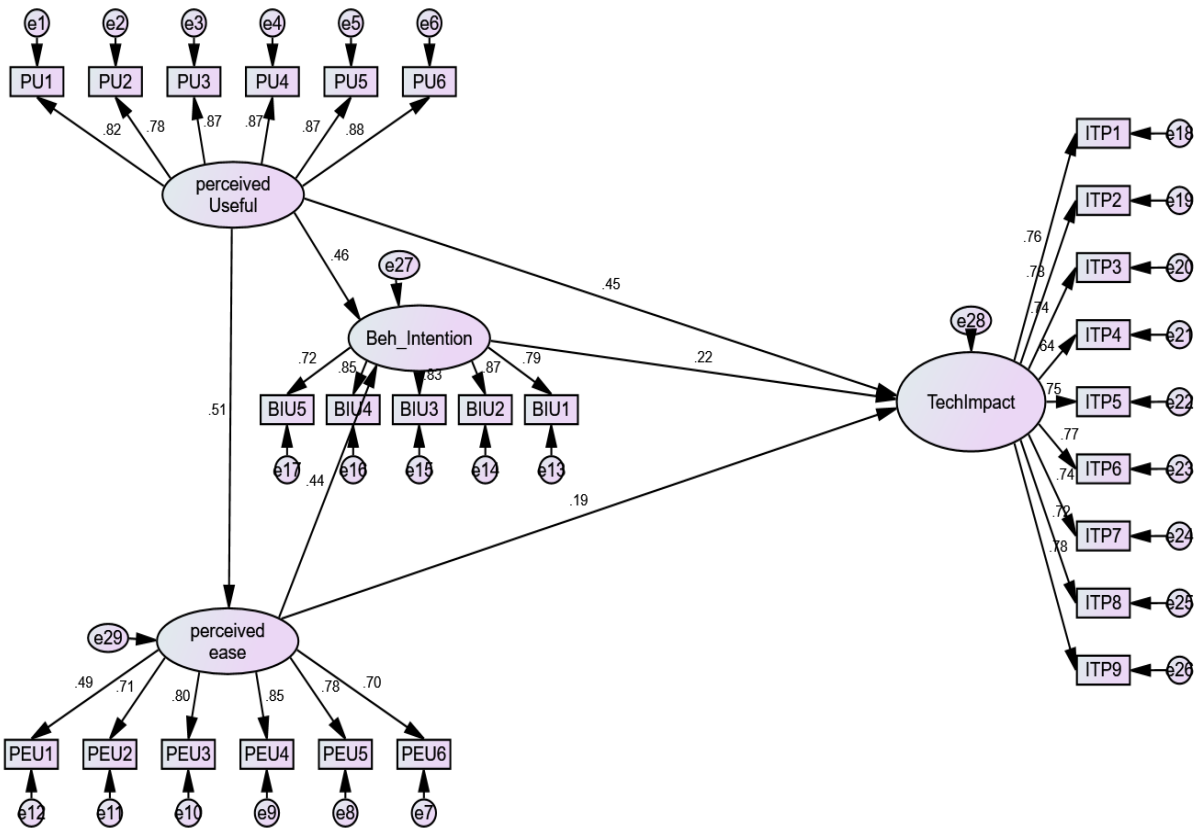

Figure 2. Path analysis using AMOS (Main Model 1)

In LISREL, latent variables were used to model relationships. After creating the main structural model 1, the more restrictive alternative models 2 to 4 were generated by fixing the designated

paths to zero (by removing them), as outlined earlier. The reason for fixing these paths is to vary the effects of PU and PEOU on TechIMP while keeping the main causal paths intact. This helps prevent model misspecification. The main path model is shown in Figure 3.

To evaluate the results of the analysis, the procedure for the χ2 difference test was also applied (Equations 1 to 4).

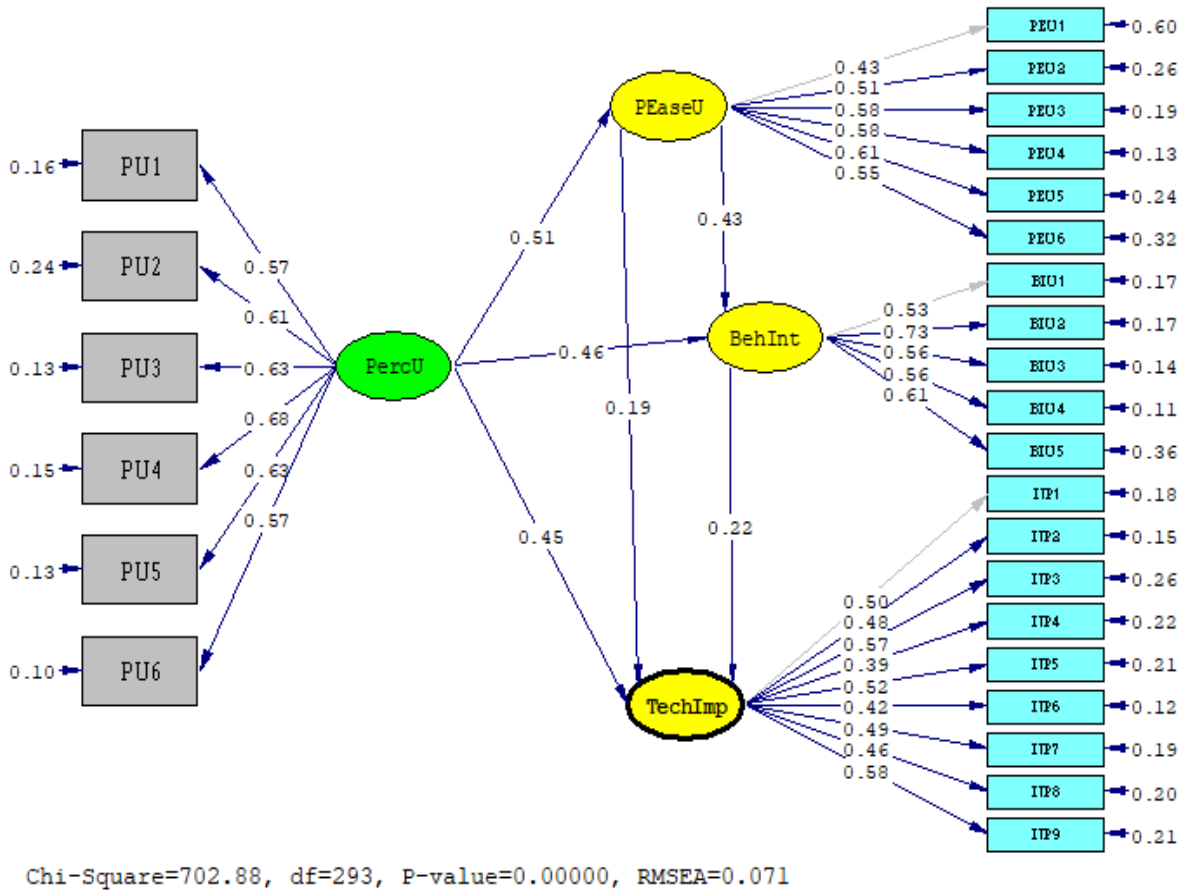

Figure 3. Path analysis using LISREL (Main Model 1)

4. RESULTS AND DISCUSSION

The measurement model was assessed for fit using LISREL and AMOS. In LISREL, the fit indices were SRMR=0.062, RMSEA=0.071 [0.064, 0.077], CFI=0.98, and TLI=0.98. In AMOS, the values were SRMR=0.062, RMSEA=0.068 [0.061, 0.075], CFI=0.93, and TLI=0.92. Both models showed adequate fit as recommended by Hu & Bentler (1999). The fit indices from LISREL were higher than those from AMOS. According to Clayton & Pett (2008) and Byrne (2001), LISREL outputs tend to be higher than those from AMOS.

Based on the findings (Figures 2 and 3), it is observed that all standardized path coefficients for causal relationships from AMOS and LISREL outputs were similar in size, although they were

larger in LISREL (see Appendix). Generally, similar to the measurement model estimates, the parameter estimates from LISREL are noticeably higher than those from AMOS; however, both produce similar results (Byrne, 2001; Clayton & Pett, 2008).

However, the model fit parameters showed reasonable differences, as shown in Tables 1 and 2. For example, the main structural model had a $\chi 2$ value of 675.08 in AMOS, compared to 702.9 in LISREL. The RMSEA from AMOS was 0.068, with a 90% C.I. [0.061, 0.075], versus 0.071 from LISREL, with a C.I. [0.064, 0.077]. Other differences between AMOS and LISREL included fit indices like TLI (0.918 vs. 0.980) and CFI (0.926 vs. 0.980). These differences were also clear in models 2, 3, 4, and 6. Nonetheless, the overall model fit, based on the outputs from AMOS and LISREL, was similar, considering that differences in values are due to variations in how the software, AMOS and LISREL, process calculations using the same data (Byrne, 2001; Clayton & Pett, 2008).

Also, based on the model fit criteria for CB-SEM, all models (Main Model 1, the three nested models [2, 3, and 4], and the non-nested model 6) met the criteria. This shows that the alternative models fit the data well and provide a good representation of reality. Therefore, choosing a model depends on the proposed study's theoretical framework, the criteria for model specification, and the researcher's goals. These alternative models offer additional insights into gaps not initially considered by the researcher, thus broadening the scope of the inquiry. Conversely, if only the main model stands out in terms of model fit, it allows the researcher to clearly justify the model specification (Roberts & Grover, 2009; Rigdon, 2023; Sarstedt et al., 2024). Given the 'positive' model fit results (meaning all models fit adequately), it's clear that a good-fitting model does not necessarily meet the theoretical specifications needed to study a specific phenomenon (Nuzzo, 2015).

Table 1.
Evaluation of Model Fit Measures Using AMOS

Measures	Threshold	Model 1	Model 2	Model 3	Model 4	Model 6
$\chi 2$		675.11	725.62	718.34	683.08	683.08
df		293	295	294	294	294
$\chi 2$/df	<3	2.30	2.46	2.44	2.32	2.32
SRMR	< 0.08	0.062	0.083	0.081	0.066	0.066
RMSEA	< 0.08	0.068	0.072	0.072	0.069	0.069
CFI	> 0.90	0.93	0.92	0.92	0.93	0.93
TLI	> 0.90	0.92	0.91	0.91	0.92	0.92
Inference	Ideal fit	good fit	good fit	good fit	good fit	good fit

Note: RMSEA confidence intervals are- Model 1 [0.061, 0.075], Model 2 [0.065, 0.079], Model 3 [0.065, 0.078], Model 4 [0.062, 0.075], Model 6 [0.062, 0.079]. Model fit is considered 'good' if the cut-off values of at least three fit measures (SRMR, RMSEA, CFI, and TLI) are attained or satisfied (Gaskin et al, 2025)

Table 2.
Evaluation of Model Fit Measures Using LISREL

Measures	Threshold	Model 1	Model 2	Model 3	Model 4	Model 6
χ2		702.88	763.87	759.91	708.39	708.39
df		293	295	294	294	294
χ2/df	<3	2.4	2.59	2.58	2.41	2.41
SRMR	< 0.08	0.062	0.083	0.081	0.066	0.066
RMSEA	< 0.08	0.071	0.075	0.075	0.069	0.071
CFI	> 0.90	0.98	0.98	0.98	0.98	0.98
TLI	> 0.90	0.98	0.97	0.97	0.98	0.98
Model Fit	Ideal fit	good fit	good fit	good fit	good fit	good fit

Note: RMSEA at 90% confidence intervals are- Model 1 [0.064, 0.077], Model 2 [0.069, 0.082], Model 3 [0.069, 0.082], Model 4 [0.064, 0.078], Model 6 [0.064, 0.078]. Model fit is considered 'good' if the cut-off values of at least three fit measures (SRMR, RMSEA, CFI, and TLI) are attained or satisfied (Gaskin et al, 2025)

Further analysis of Tables 1 and 2 showed a strong similarity among the competing models. Notably, Models 4 and 6 have identical fit values in both the AMOS and LISREL outputs. Their structural similarity, illustrated conceptually in Figure 1, suggests they are equivalent.

Additionally, as shown in Tables 1 and 2, LISREL reports higher fit indices than AMOS. For example, in Model 1, AMOS reported a CFI of 0.93, while LISREL reported a CFI of 0.98. This difference has been attributed to variations in computational processing between the software, AMOS and LISREL, when using the same data (Byrne, 2001; Clayton & Pett, 2008).

To differentiate among the models, the researcher employed model comparison techniques to find the best-fitting and most parsimonious model.

Table 3.
Model comparison for Nested and Non-Nested Models (AMOS)

Model		Main Model	Nested Models			Non-Nested
Measures	**Threshold**	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 6**
Δχ2			50.511	43.228	7.965	
Δdf			2	1	1	
Significance	$p < 0.05$		$p<0.001$	$p<0.001$	$p<0.01$	
AIC	lower value	791.11				797.08
Preferred			Model 1	Model 1	Model 1	Model 1

Using AMOS and LISREL, the main Model 1 was compared with the nested models (2, 3, and 4) through a χ2 difference test and with the non-nested Model 6 using AIC. The χ2 difference test results indicated that Model 1 was significantly better than Models 2 ($p<0.001$), 3 ($p<0.001$), and 4 ($p<0.01$). This suggests that imposing constraints on Models 2, 3, and 4 by fixing or removing paths significantly decreased model fit. In other words, the additional paths in the main Model 1 enhanced the model's fit to the sample data. The results also showed that LISREL generally produced higher Δχ2 estimates than AMOS.

Table 4.
Model comparison for Nested and Non-Nested Models (LISREL)

Model		Main Model	Nested Models			Non-Nested
Measures	**Threshold**	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 6**
Δχ2			60.99	57.03	5.51	
Δdf			2	1	1	
Significance	$p< 0.05$		$p<0.001$	$p<0.001$	$p<0.01$	
AIC	lower value	818.88				822.39
Preferred			Model 1	Model 1	Model 1	Model 1

Furthermore, the non-nested Model 6 was compared with Model 1 using the AIC as the criterion. Model 1 is preferred because it has a lower AIC value (AMOS: 791.11 vs. 797.08; LISREL: 818.88 vs. 822.39) than Model 6.

It is important to remember that researchers should not solely depend on model fit statistics when selecting a model, but also verify that the alternative model is based on solid theoretical foundations or represents a contradicting theory (Weston & Gore, 2006; Oamen, 2024).

Implications for behavioral and management Researchers

Researchers in the social and behavioral sciences can gain several advantages from deliberately comparing competing structural models in their research. At a basic level, this approach provides information that helps researchers improve model fit by trimming, re-specifying, and applying a theoretical framework. This allows them to distinguish between a poorly developed and a well-developed model. During model development and hypothesis testing, evaluating alternative models against the initially hypothesized model enables researchers to assess the strength of the proposed model relative to other plausible options.

Similarly, this methodology promotes the development of new theories and the validation of new hypotheses because competing models can reveal insights and dimensions of knowledge that were not initially anticipated or captured before analysis. Conversely, it enhances the refinement of existing preferred models when alternative models are thoroughly examined. This approach assists the researcher when the initially proposed model does not fit well, leading to modifications. In such cases, the competing (alternative) models may become the ideal choice. Finally, based on the reliable output and information produced by this approach, managers and policymakers can avoid making mistakes or quick judgments based solely on the results of a specific study. Instead, information about alternative models will allow them to consider different perspectives or "other sides of the same coin".

Recommendations of the study

Based on the findings of this paper, it is advised that researchers explore and report alternative structural models in their studies. This approach can create new opportunities and perspectives for further research through model comparisons (Nuzzo, 2015). This paper is unique because it offers a simplified, easy-to-understand, and user-friendly analytical format for researchers who may not be experts in SEM but want to enhance and test structural models. Additionally, applied researchers can trust the fit statistics of their models more due to the transparency, rigor, and robustness of this method (Rigdon et al., 2020; Rigdon, 2023). Lastly, based on this study, the authors suggest using the reporting format (shown in Tables 1 or 2, and Tables 3 or 4 for AMOS and LISREL, respectively) when writing research papers.

5. CONCLUSION

This illustrative methodological study examined the comparison of competing (alternative) structural equation models as a strategy to support a robust and rigorous assessment of structural models. The results of this study justify the methodological importance of including and reporting competing (alternative) structural models before deciding whether to retain the initially hypothesized structural model. This contradicts the stance of Gaskin et al. (2025). The findings of this illustrative study promote transparency in reporting models and reduce the biased use of selective indices to justify poorly specified models.

Limitations of the study

Maximum likelihood estimation was the default estimation technique used for this analysis in both AMOS and LISREL. Because the maximum likelihood estimator assumes normality, it does not account for nonnormal data. Since non-normal distributions are common in practice, researchers are advised to use robust maximum likelihood estimators or appropriate bootstrapping methods to estimate their models, along with baseline checks for possible normality concerns. Therefore, researchers should consider alternative methods available in the literature (Shipley, 2000; Rigdon, 1999; Pavlov et al., 2020; Collier, 2020) when normality is violated. Finally, this study was based on CB-SEM, and as a result, different estimates will be obtained if PLS-SEM methodology is applied (Sharma et al., 2019, for more information). Therefore, researchers should choose the methodology that suits their purpose and dataset (Sarstedt et al., 2024).

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Appendix

Table. Path relationships between constructs (standardized coefficient values)

Path	β (LISREL)	β (AMOS)	p-value
PU to PEOU	0.510	0.492	<0.001
PU to BIU	0.460	0.429	<0.001
PEOU to BIU	0.430	0.419	<0.001
BIU to TechIMP	0.220	0.206	<0.01
PEOU to TechIMP	0.190	0.174	<0.01
PU to TechIMP	0.450	0.399	<0.001

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