



Quality Assurance in the Reporting of Structural Equation Path Models: A Reviewer's Perspective based on LISREL Analysis

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Abstract

Maintaining the transparency, reliability, and replicability of knowledge in research papers and manuscripts is critical to the credibility of scientific output. This paper emphasizes the importance of preserving the integrity and transparency of path model results from structural equation modeling (SEM), a key statistical tool for researchers. SEM offers researchers an advantage in testing hypotheses across variables with simple and complex multivariate relationships. However, this popularity could lead some researchers to report results that inaccurately reflect SEM outputs, possibly due to limited knowledge of SEM and/or the urgency to produce statistically significant results. Therefore, to maintain research integrity and transparency, editors, reviewers, and the research community should be aware of this potential issue. To address this challenge, results from SEM path analysis should be verified by examining the correlation and/or covariance matrices presented in the summary data. This paper illustrated this approach in LISREL using covariance-based SEM to analyze a path model from a published paper. This paper recommends this approach as the norm for users, prospective users, editors, reviewers, and consumers of SEM tools and outputs. Additionally, several key recommendations for maintaining the quality and integrity of structural path models reported in the manuscripts submitted for possible publication in journal outlets were outlined.

Keywords: Correlation Matrix, LISREL, Research Integrity, Structural Equation Modeling, Summary Data

RESEARCH ARTICLE

1. Introduction

Globally, structural equation modeling (SEM) is a widely used multivariate statistical technique among researchers. This popularity stems from its ability to model complex relationships, ensure statistical accuracy, and be relatively easy to use (Hair et al., 2019; Zhang et al., 2020). Compared to basic regression methods, SEM provides more precise estimates of multivariate relationships while accounting for measurement error (Dash & Paul, 2021). SEM comes in two forms: covariance-based structural equation modeling (CB-SEM) and partial least squares structural equation modeling (PLS-SEM). CB-SEM is based on the common factor principle, whereas PLS-SEM relies on composites; however, both SEM types yield similar results. CB-SEM is particularly useful for theory building, model comparison, and development, although it can be sensitive to small sample sizes (Gaskin et al.,

2025). Conversely, PLS-SEM is advantageous for theory development and predictive modeling and tends to perform well with small samples (Dash & Paul, 2021). SEM outputs are typically presented as path models, which can include latent constructs, composites, and full structural path models (Collier, 2020).

Despite the inherent flexibility of path analysis using SEM techniques, researchers need training, ongoing practice, and expertise to produce reliable results. This challenge may lead researchers to generate suboptimal, imprecise, or inaccurate outcomes by manipulating data or statistical results to achieve the 'desired' or 'expected' outcomes. Similarly, the pursuit of statistically significant results can increase the risk of output manipulation. This practice undermines the reliability and acceptance of SEM results within the scientific community and among policymakers who rely on scientific information to make well-informed decisions that affect people's lives (Ioannidis, 2005). By extension, it is imperative to detect this practice early and address it adequately to prevent misleading inferences, flawed theoretical contributions, and faulty policy decisions from occurring and persisting.

Therefore, editors and reviewers should be aware of this possibility and identify ways to counteract this trend. One method to address this gap is to verify SEM analysis results with summary data. Summary data provide essential information about the variables in a study (Collier, 2020; Joreskog & Sorbom, 2022). The summary data include a correlation and/or covariance matrix, mean, standard deviation, variance, and sample size.

According to Armond et al. (2024), transparency and reproducibility of research outputs are fundamental for enduring and reliable research. Therefore, this paper proposes this approach as a standard practice for users, prospective users, and consumers of SEM outputs. To demonstrate this, a retrospective path analysis of a published study using the correlation matrix is presented. The broader implication of this paper is that it will benefit the research community by promoting the use of summary data to verify and ensure the integrity and quality of results obtained from SEM analysis.

The importance of this proposed approach lies in its support for the replicability and reproducibility of SEM research. Therefore, this research output gives readers, fellow researchers, and policymakers confidence in its use.

The purpose of this paper is twofold: first, to demonstrate how to verify results from a published study using summary data. Second, to provide recommendations to journal editors, reviewers, and researchers.

2. Methodology

This illustrative study used the correlation matrix from a published paper by Oamen (2023) that focused on the Technology Acceptance Model. The matrix was used to replicate the structural path model presented in the publication. It provided the essential summary data needed to replicate the analysis using covariance-based SEM, specifically Linear Structural Relations (LISREL) (Joreskog & Sorbom, 1996; Joreskog & Sorbom, 2021). Additionally, compared with the covariance matrix, the correlation matrix offers more efficient parameter estimates with higher statistical power in LISREL (Yuan & Zhang, 2025).

The variables for this analysis were perceived usefulness (PU), perceived ease of use (PEOU), Behavioral Intent to Use (BIU), and Technology Impact on Performance (TechIMP), collected from 282 pharmaceutical marketing executives in Nigeria. The initial model was estimated using WarpPLS (Kock, 2022). The path model from the study is presented in Figure 1.

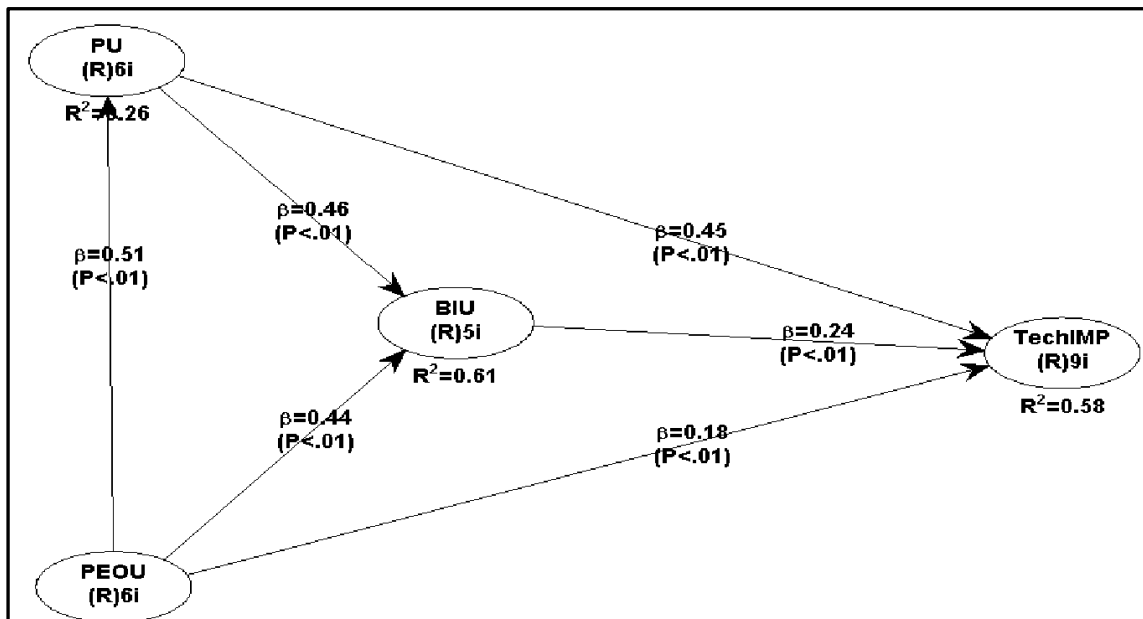


Figure 1. Path diagram of Technology Acceptance Model (Oamen, 2023; obtained with permission)

The goal of the replication was to verify the path relationships in the study model by Oamen (2023) using the summary provided in LISREL.

The procedure for analysis using LISREL syntax is summarized (see Figure 2) as follows.

1. First, 'open the file', 'click on open', then click on syntax, and click 'ok'.
2. Then the 'blank syntax screen' opens. On the blank screen, the 'Title line' is created.
3. Below the title line, the list of variables in the order they appear on the correlation matrix is listed.
4. A new line called 'Correlation Matrix' is created.
5. On the next line, write the correlation matrix. ENSURE '1.00' runs across the diagonal of the matrix. Also, remove zero before the decimal point (e.g., .05 instead of 0.05).
6. After the correlation matrix, the next line, called the 'Sample Size', is presented (sample size: 282).
7. The next line is the structural path relationships (paths between variables based on theorized relationships, e.g., $y_1 = c_1 c_2$, which means that y_1 is regressed on or predicted by c_1 and c_2).
8. The next line is 'OPTIONS: SC EF' (standardized coefficients and output).
9. The next line is 'Path Diagram'.
10. The final line is 'End of Problem'.
11. Then, click 'RUN LISREL'.

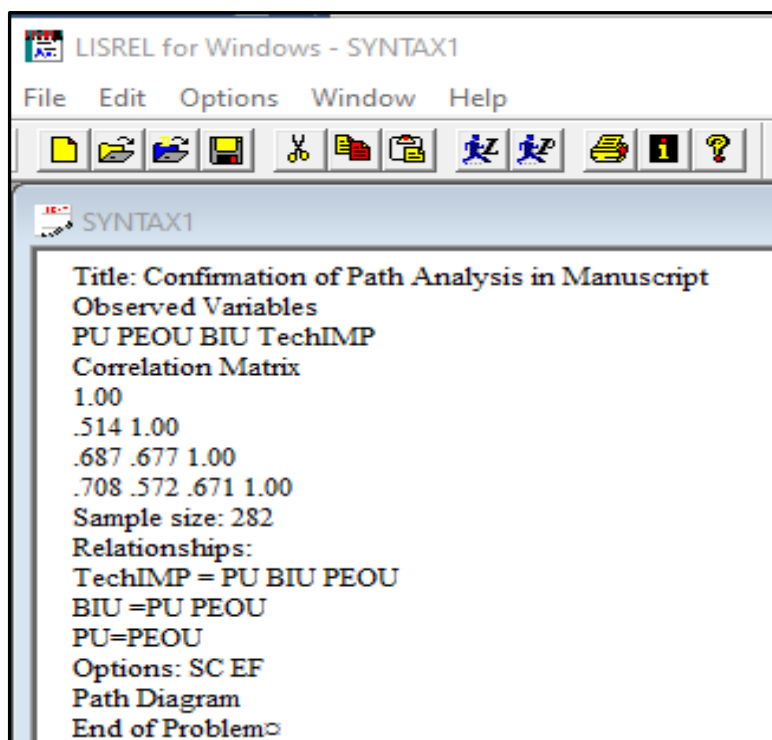


Figure 2. LISREL syntax for Summary Data

Table 1. Correlation Matrix of Technology Acceptance Model

Constructs	PU	PEOU	BIU	TechIMP
PU	1			
PEOU	0.514***	1		
BIU	0.687***	0.677***	1	
TechIMP	0.708***	0.572**	0.671***	1

Note: Reference-Oamen (2023), ***p < 0.001

The correlation matrix in Table 1 reveals the significant intercorrelations among the variables. The ‘1’s along the diagonal represent the value of the variable correlated with itself. The presented Matrix is the primary summary data that shows possible causal relationships in the hypothesized model. This information was presented in syntax as shown in Figure 2.

3. Results and Discussion

In this section, the results from the syntax in Figure 2 are presented. In Figures 3 and 4, the path diagrams depict the positive and significant relationships among the variables (PEOU to PU; PU to BIU; PEOU to BIU; BIU to TechIMP; PU to TechIMP; and PEOU to TechIMP), consistent with the path model outlined in Figure 1.

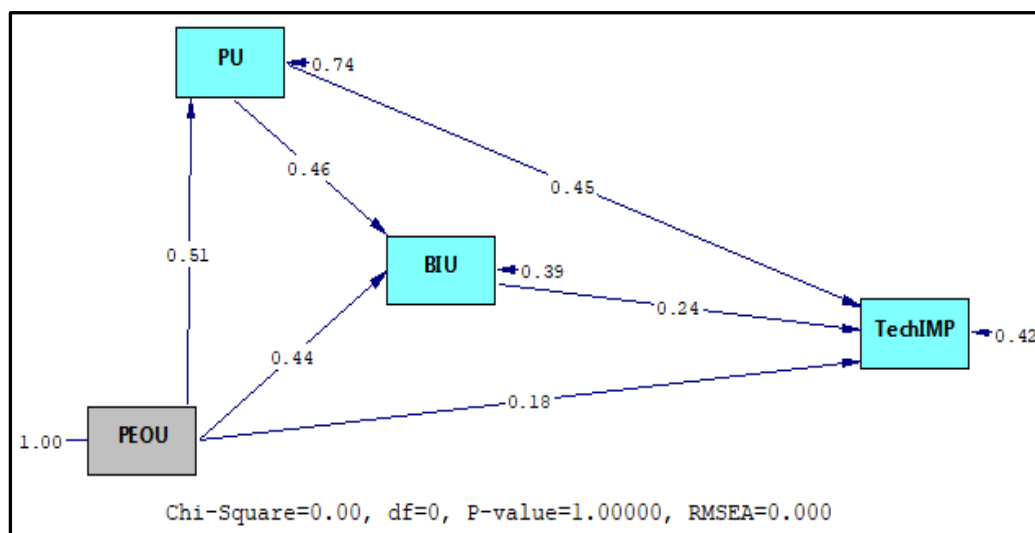


Figure 3. LISREL output of the Technology Acceptance Model using sample data (beta values)

Figure 4 shows the t -values corresponding to the same significance levels (p -values) as those of the path model under scrutiny. In other words, the model being studied produced the same outcomes as those generated from summary data using LISREL.

Therefore, editors, reviewers, and researchers can apply this method to verify the results of SEM path analysis. An advantage of this method is that it requires only basic input data; unlike raw data, it is faster and more practical under time constraints.

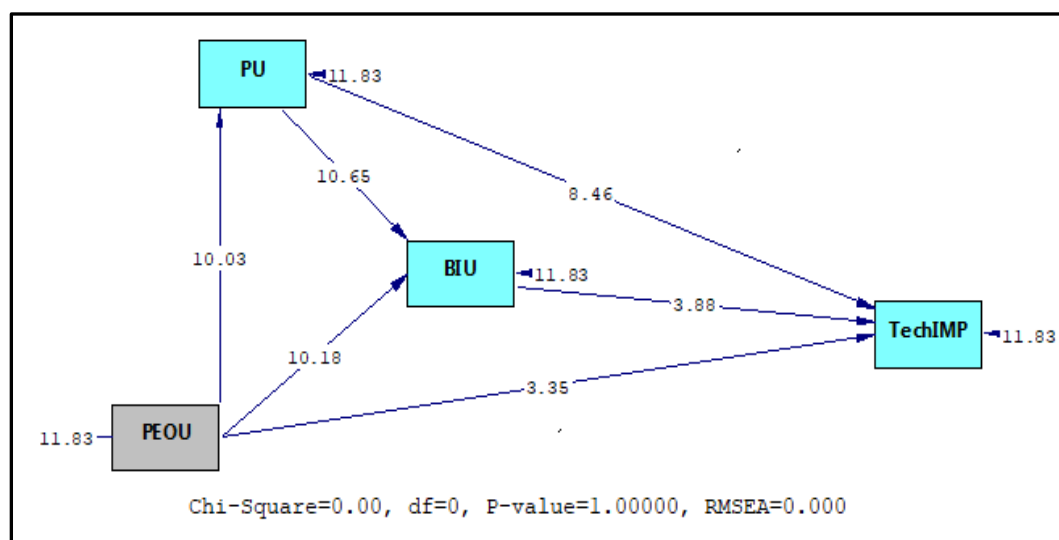


Figure 4. LISREL output of the Technology Acceptance Model using sample data (t -values)

4. Recommendations

1. The inclusion of the Correlation and Covariance Matrices as a key report is strongly recommended. Authors should be required to submit these matrices (and/or any relevant summary data) as a mandatory requirement for manuscript consideration.
2. Summary data, which includes the mean and standard deviation, should also be provided for evaluation.
3. Editors and Reviewers should be presented with soft copies of the dataset to verify results.

4. It is advisable that the software-generated path diagrams should be used instead of the authors' own drawings. This approach will minimize the likelihood of altering path coefficients, significance levels, and *t* or *z*-values.
5. Reviewers should be encouraged to verify path relationships by using the matrices provided. Hence, journal editors should find ways to incentivize thorough reviews.
6. In cases where the path diagrams are too crowded or unpresentable due to model complexity, the originally generated diagram and the redrawn diagrams should be presented for review.
7. Selection of reviewers should be based on proven capacity and expert knowledge of SEM.
8. Researchers should form the habit of verifying and confirming their own analysis by using summary data.

5. Conclusion

The purpose of this illustrative study was to highlight the importance of evaluating path analysis models in manuscripts using SEM and to outline a simple procedure to assist editors and reviewers. This recommended practice will support the verification of the validity of SEM analysis results presented in manuscripts submitted for review, thereby fostering research integrity and transparency. The study demonstrated how to analyze results from a published path analysis study using the CB-SEM software LISREL. This paper recommends adopting this method as a standard practice for users, prospective users, editors, reviewers, and consumers of SEM outputs. However, readers should note that only the CB-SEM methodology in LISREL was used for analysis in this illustrative study. Therefore, manuscripts with results analyzed with PLS-SEM should be verified using PLS-SEM software.

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