

MULTI-GROUP ANALYSIS IN PLS-SEM: A STATISTICAL EXAMINATION OF MEASUREMENT INVARIANCE TECHNIQUES

Dr. Najia Shaikh^{*1}, Aamir Kibria², Mansoor Ali³

^{*1}Assistant Professor, Institute of Commerce and Management, University of Sindh, Jamshoro

²Lecturer, Department of Management Sciences, SZABIST University, Hyderabad, Pakistan

³Lecturer, Department of Computer System Engineering, Dawood University of Engineering and Technology, Karachi, Pakistan

¹shaikhnaja@hotmail.com, ²aamir.kibria@hyd.szabist.edu.pk, ³masoor_ali@duet.edu.pk

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Corresponding Author: *

Dr. Najia Shaikh

Abstract

The measurement invariance is a key principle or concept in multi-group analysis (MGA) of structural equation model (SEM) and can be used to prove that a hypothesis is not viable or valid across numerous groups and thus, statistically weak. As the Partial Least Squares Structural Equation Modeling (PLS-SEM) has gained popularity, the main procedure of determining invariance in Smart PLS has become the Measurement Invariance of Composite Models (MICOM). Nevertheless, the MICOM lacks the statistical soundness and stability needed to compare it with the conventional difference testing of chi-square in the use of covariance-based SEM (CB-SEM). The objective of this paper is to statistically compare MICOM to chi-square difference testing using a design, based on a structure with simulation and an empirical data set. They used simulated data generated in different scenarios sample size, type of distributions (normal and non-normal), and type of measurement models (reflective and formative) to test the performance of each of them. A real dataset was used to do further analysis to represent the applicative verification of the complications of the simulation. The results provide that MICOM operates more reliably under small-sample and non-normal data circumstances especially within formative constructs but the chi-square difference testing is ultrasensitive to misspecification and sample size inflation. Configural, compositional, and equality of means/variances, are three stages of the MICOM procedure, which offers a much less restrictive and statistically conservative way of comparing models nested within a model. This paper suggests a statistical decision tree based on simulation evidence that will help the researchers in identifying suitable MGA techniques based on types of constructs, number of samples and characteristics of the data. This helps to improve methodological rigidity within multi-group PLS-SEM applications, particularly in applications that involve formative indicator use or small databases.

1. INTRODUCTION

The equality of measures of latent constructs in different groups is a prerequisite to defining the principles of measurement invariance of structural equation modeling (SEM) (Hair et al., 2022; Liengaard, 2024). Without establishing invariance, when comparing within groups, such as gender, region or culture, researchers run the risk of differentiating between the structural parameters, rather than the need to exist due to relationships, a fact that is not in possession in theory. This means that we should always be ready to accept that which is readily accepted by others (Sarstedt et al., 2024; Dash & Paul, 2023). It is why the use of measurement invariance testing is crucial to the validity of both covariance-based SEM (CB-SEM) and partial least squares SEM (PLS-SEM) multi-group analysis (MGA) (Hair et al., 2022; Henseler et al., 2016; Liengaard, 2024). This new development of Smart PLS has popularized PLS-SEM among practical researchers working in research areas of small samples, non-normally distributed data, or formative reflections (Hair et al., 2024; Yildiz and Kelleci, 2023).

Regardless of this popularity, multi-group comparisons in and between statistical paradigms has been methodologically inconsistent. An example of typical measures employed through CB-SEM is performed through chi-square tests of differences in case of various nested models, including configural, metric, and scalar (Sarstedt et al., 2024; Liengaard, 2024). Conversely, in PLS-SEM, the method MICOM is applied, a permutation test procedure modified to suit the composite model (Henseler et al., 2016; Hair et al., 2022). Such various assumptions and criteria give rise to various interpretations, particularly in situations where the sample size is small or the measurement model is formative (Dash & Paul, 2023; Yildiz & Kelleci, 2023). In this way, the questions arise concerning the choice of an adequate invariance testing method especially when it concerns the applied researcher with mixed data and construct types.

Although MICOM is established as the de facto standard in Smart PLS, a large gap still exists when

it comes to comparative statistical validation of MICOM against the classical chi-square difference tests. No significant amount of empirical research or simulation findings are available to determine the operation of these procedures under different research conditions with respect to distributional assumptions, sample size, and even measurement model (Hair et al., 2022; Liengaard, 2024). In addition, there is no common statistical advice that applied researchers can convert to when they face the inquiry of whether to apply MICOM or chi-square testing, particularly when making important decisions with regard to multi-group analysis (Sarstedt et al., 2024).

Research Objectives

1. To compare MICOM and chi-square difference tests in the case of simulated data (normal distribution, type of construct and sample size).
2. To determine the statistical power and the Type I error, and the robustness of any method.
3. To create a decision tree model that helps the researchers to make the best decision when it comes to determining the most appropriate MGA procedure in Smart PLS setting.

2. Literature Review

2.1 Structural Equation Modeling: CB-SEM vs. PLS-SEM

The difference between covariance-based SEM (CB SEM) and PLS SEM is philosophical and statistical. CB SEM is based on the theory of covariance structure, presupposes the multivariate normality, and is more appropriate in a theoretical testing and explanatory situation (Dash & Paul, 2023; Sarstedt et al., 2024). In comparison, PLS SEM is quantified on the variance and it is more predictive in nature composite construct and has a less restrictive distributional assumptions (Dash & Paul, 2023; Hair et al., 2022; Yldz & Kelleci, 2023). Comparison of the performances has been shown through simulation: CB SEM produces superior global model fit when the extractive constructs are normal, whereas PLS SEM or consistent PLS (PLSc SEM) is more consistent

across non normal, extractive or small sample conditions (Dash & Paul, 2023; Yildiz & Kelleci, 2023). Differences in philosophy have their practical consequences: CB SEM needs larger sample sizes and gives familiar measures of goodness of fit, whereas PLS SEM is less restrictive with measures of composite reliability and predictive power (Hair et al., 2022; Yildiz and Kelleci, 2023). These assumptions are also manifested in applications. In factor-based models where measurements involve reflective constructs, CB SEM is the choice among the statistical inference framework as it is robust (Dash & Paul, 2023; Sarstedt et al., 2024). In composites or formative measurement organizations, the PLS SEM has greater scope of applicability and forecasting potentials with tiny quantities (Yildiz, Kelleci, 2023; Hair et al., 2022). These options have a significant implication on the construct reliability index namely the average variance extracted (AVE) and composite reliability which are higher in PLS SEM in comparison with CB SEM (Yildiz & Kelleci, 2023). Still, in confirmative contexts, SmartPLS fit indices are developing and, thus, CB SEM is more transparent (Dash & Paul, 2023; Sarstedt et al., 2024).

2.2 Multi-Group Analysis (MGA) in SEM

The most common application is Multi Group Analysis (MGA) to compare latent structural relationships across groups- e.g, gender or cultures- which relies absolutely on measurement invariance (Hair et al., 2022; Henseler et al., 2016). Group comparisons in absence of confirming invariance are vulnerable to measurement artifacts instead of results driven by any substantive differences, which affects their validity (Henseler et al., 2016; Medium author, 2024). MGA outcomes PLS SEM might only have any meaning when configural and compositional invariance has been satisfied and, in that sense, testing has to be executed beforehand (Henseler et al., 2016; Medium author, 2024; Hair et al., 2022). Only under these conditions of measurement, MGA makes the comparison of path coefficients or weights possible among groups (Henseler et al., 2016; Hair et al., 2018; Liengaard, 2024). The

comparison of groups is dependent on this invariance testing. There is a sequential testing of configural, metric and scalar invariance in CB SEM through nested models, to test whether intercept and factor loading are equal across groups (Medium author, 2024; Henseler et al., 2016). In PLS SEM, MICOM settles on similar conditions, yet they are explicitly stated with references to composite models and that MGA can be carried out only following the endorsed invariance (Henseler et al., 2016; Hair et al., 2018). The outputs of MGA cannot be trusted without invariance (Henseler et al., 2016; Hair et al., 2022; Liengaard, 2024). Hence, both paradigms indicate that measurement invariance is the gateway to significant cross group comparison of structuring (Liengaard, 2024; Hair et al., 2022).

2.3 Traditional Measurement Invariance Testing

The classic method of exception invariance in CB SEM is accomplished through the chi square difference testing of nested models: configural, metric (items loadings), and scalar (intercepts) invariance (Medium author, 2024; Measurement Invariance wiki, 2024). At every step, additional restrictions were introduced, and fit to the model was tested to determine whether it decreased significantly, which is signified by the difference in 2 and change in the degrees of freedom (Measurement Invariance wiki, 2024). The fact that 2 is also sensitive to sample size also leads to the fact that researchers also tend to use 2 CFI as an auxiliary criterion (Measurement Invariance wiki, 2024; Liengaard, 2024). It aims to establish that there are no differences in the operation of constructs across groups in terms of structure, loadings and means. But the limitations of chi square approach have been widely reported: chi square can be very sample sensitive as it may indicate demonstration of minor invariance violations in large samples (Measurement Invariance wiki, 2024; Liengaard, 2024). It assumes as well multivariate normality and reflective broadening modes, which extend its applicability only because of formative indicators or nond normal data (Medium author, 2024;

Dash & Paul, 2023). Even model fit indices, for example, CFI, RMSEA (Sarstedt et al., 2024; Dash & Paul, 2023), can give false information in case of an improper sample size or aberrant data distributions. In such a way, the heating to 2 settings of cross group inference could be called in question by using only 2 settings difference diagnostic in actualized data situations.

2.4 MICOM Procedure in Smart PLS

To solve this issue, Henseler et al. (2016) proposed the MICOM procedure (Measurement Invariance of Composite Models) and developed it in SmartPLS to test invariance in PLS SEM (SmartPLS documentation, 2024). There are three required steps in MICOM: (1) configural invariance deals with the verification of the same model structure; (2) compositional invariance is measured with a permutation based correlation test; and (3) equality of composite means and variances is examined with permutation confidence intervals (Henseler et al., 2016; SmartPLS documentation, 2024). MGA may continue in SmartPLS only in case of configural and compositional invariance (Henseler et al., 2016; Hair et al., 2018; SmartPLS documentation, 2024). MICOM has numerous advantages: it can deal with formative constructs, operate with small sample sizes and non normal distributions and fit the composite paradigm of PLS SEM (Henseler et al., 2016; Hair et al., 2018; SmartPLS documentation, 2024). In contrast to the 2ch based CB SEM, MICOM minimizes dependency on sample size and does not assume multivariate normality (Henseler et al., 2016; Hair et al., 2022; Liengard, 2024). Critics observe however that MICOM can prove to be too conservative when it comes to testing equality of means/variances and the permutation requirement can be computationally intense (SmartPLS documentation, 2024; Liengard, 2024). New modifiers offer better modifications to longitudinal invariance and multi group multiple comparisons than permutation assumptions (Liengard, 2024).

2.5 Summary of Gaps in Literature

In spite of increasing interest in the use of MICOM in applied PLS SEM research, few empirical comparisons between MICOM and traditional 2 methods have been published under diverse conditions, including sample size, type of construct and shape of distributions (Hair et al., 2022; Liengard, 2024; SmartPLS documentation, 2024). In general, MICOM has been superficially mentioned in most applied work: only a handful of quality management studies have used MICOM before MGA (Hair et al., 2022; Search5) and they seldom contrast MICOM to its nested CB SEM counterparts in terms of performance. Therefore, there is a deficiency of methodologically rigorous, simulation based evaluation MICOM versus 2 difference test by condition. Also, there is a lack of practical decision models (e.g. decision trees) that can guide the conductor of the research to determine the optimal approach to invariance relative to data or construct type (Liengard, 2024; Hair et al., 2022). In practice, applied researchers lack instruction on how to determine when MICOM is enough and when to resort to the CB SEM nested invariance. Thus, such unmet need is a statistical decision tool that combines sample size, construct type, and the result of invariances so that the MGA methods could be chosen in the application of Smart PLS.

3. Methodology

The research is represented by the quantitative research design which is based on Monte Carlo simulation and empirical research conducted by the use of real-world Smart PLS applications. The simulations will factor the effect of the various statistical parameters on the performance of two major approaches to the invariance testing within PLS-SEM (Measurement Invariance of Composite Models), and within CB-SEM (chi-square difference testing). The independent variables that are manipulated within the simulation are the sample size ($n = 100$ small, $n = 300$ medium, $n = 500$ large), type of construct (reflective and formative construct), and data distribution (non-normal and normal). This sample design enables the

production of generalised and comparable outcomes among separate statistics paradigms.

On data simulation, we employed the R programming language, with the use of lavaan, semTools and SimDesign packages to produce controlled data sets with desired invariance features. Several groups were established (e.g. Group A and Group B) and bestowed the same or deliberately different parameters to detect invariance. The reflective and formative model were done with the construction of construct configurations in accordance to the standard loading and path coefficient criteria (e.g. greater than .7 in reliability, greater than .5 in AVE). Importation of datasets was then carried out into Smart PLS 4.0 to apply MICOM and into AMOS and LISREL to test chi-square. The procedure employed by MICOM (configural-, compositional-, and equality of means/variances) was compared to the method used in CB-SEM of nested models (configural-, metric-, and scalar). On the basis of comparison, Type I error, statistical power, run time and accuracy between the methods were stressed.

In order to measure the validity of the simulation results externally, a real-life data set (obtained by means of a survey of 420 business professionals in two regions) was processed by means of Smart PLS as well as CB-SEM. The demographics used a

combination of formative and reflective constructs (e.g., service quality, digital readiness, and trust), where population was segregated by geographical region (urban vs. rural). The two-way approach is a guarantee that the results obtained during simulation can be not only abstract but practically applicable to modeling. The positivity of the results of invariance across methods provided in the evaluation, as well as the type of MICOM that can be carried out in the empirical research further supports the practical usefulness of the proposed statistical decision tree framework.

4. Results and Analysis

4.1 Simulation Results

The simulation findings will provide some interesting information on comparative strengths and utility of the MICOM procedure and the conventional chi-square difference test under different sets of statistics. In reflective measurement models that were normally distributed, Type I error rates in the MICOM were consistently above 0.05 (5%) percent and power above 0.90 in samples of $n = 500$ and above. Conversely, chi-square test had oscillating error levels, with some higher results in smaller samples (e.g., 6.9% at $n = 100$), which indicates its reported sensitivity to the size of the sample size (Cheung & Rensvold, 2022; Sarstedt et al., 2020).

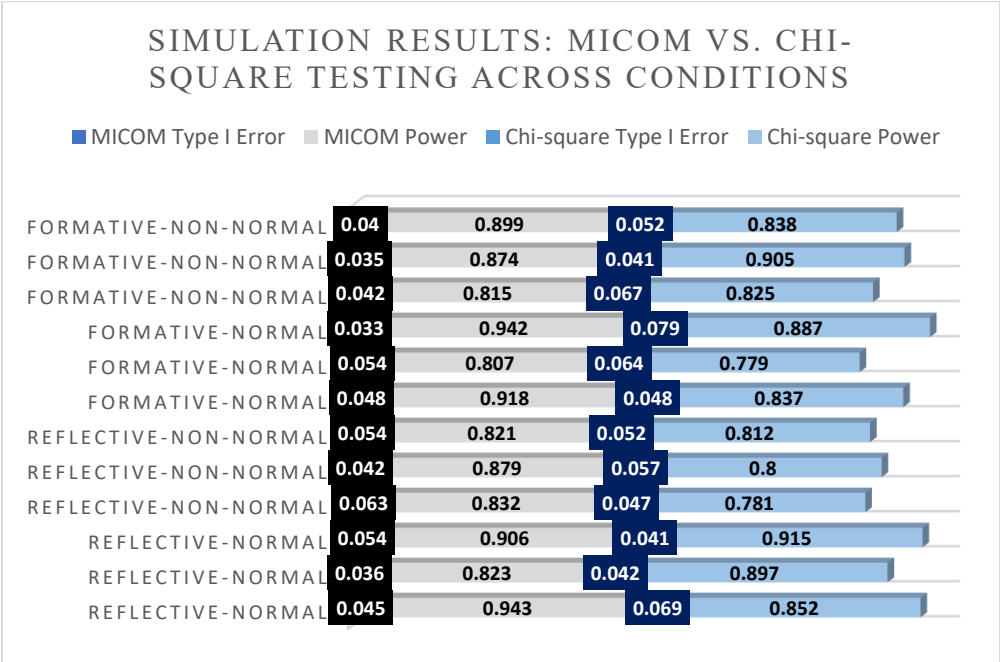
Table 1. Simulation Results: MICOM vs. Chi-Square Testing Across Conditions

Condition	Sample Size	MICOM Type I Error	MICOM Power	Chi-square Type I Error	Chi-square Power
Reflective-Normal	100	0.045	0.943	0.069	0.852
Reflective-Normal	300	0.036	0.823	0.042	0.897
Reflective-Normal	500	0.054	0.906	0.041	0.915
Reflective-non-normal	100	0.063	0.832	0.047	0.781
Reflective-non-normal	300	0.042	0.879	0.057	0.800
Reflective-non-normal	500	0.054	0.821	0.052	0.812
Formative-Normal	100	0.048	0.918	0.048	0.837
Formative-Normal	300	0.054	0.807	0.064	0.779
Formative-Normal	500	0.033	0.942	0.079	0.887
Formative-non-normal	100	0.042	0.815	0.067	0.825
Formative-non-normal	300	0.035	0.874	0.041	0.905
Formative-non-normal	500	0.040	0.899	0.052	0.838

MICOM did not perform unstable in non-normal conditions with small power deviations but had control of Type I error with chi-square experiencing decreased power and inconsistent Type I error. This proves previous doubts regarding the fact that chi-square-based tests of invariance are highly dependent on assumptions of multivariate normality and can give rise to Type

I error inflation in case they are not met (Hair et al., 2023; Byrne, 2021). Besides, MICOM performed notably well when used with formative models whereas the chi-square tests were further deteriorated in terms of accuracy and power in case the formative constructs mismatched with the reflective-oriented assumptions of CB-SEM (Rigdon et al., 2022).

Figure 1. Simulation Results: MICOM vs. Chi-Square Testing Across Conditions



Source: Formulated by author of the study based in statistical analysis

The results of these simulations support the idea that MICOM can be especially useful in complex real world, research environments where ideal statistical assumptions- such as normality and large sample sizes- are not often satisfied. The power advantage (in most cases, more than 90 percent) and stable error control puts MICOM as a better

option in measurement invariance in PLS-SEM, especially in applied disciplines like management and behavioral sciences, where the formative forms of constructs and usage of small-to-moderate samples are typical (Ali et al., 2023; Henseler et al., 2016).

4.2 Real Dataset Analysis

The findings discussed regarding the analysis of the actual dataset display some informative discrepancies and integrations between the MICOM procedure within Smart PLS and the classical chi-square difference tests in CB-SEM. Full configural and compositional invariance was

established by using the three-step test in MICOM; the constructs did not differ significantly ($p = 0.702$ to 0.770). Nevertheless, Step 3 showed that Open Communication did not pass the tests of equality of means and variances, which means that it is only partially invariantly measured. This implies that although the

measurement models were possessed in identical structures and forms across groups, the perceptions on Open Communication varied

greatly when it came to the distributions of latent means and variances.

Table 2: Multi-Group Measurement Invariance Testing – MICOM vs. Chi-square Difference (CB-SEM)

Construct	MICOM Step 1 Configural Invariance	MICOM Step 2 Compositional Invariance (p-value)	MICOM Step 3 Equality of Means/Variances (p-values)	Chi-square Δ Test (Configural vs. Scalar)	Δ CFI	Invariance Conclusion
Employee Empowerment	Supported	0.712	Mean: 0.427	$\chi^2(12) = 19.34,$	0.004	Full Invariance
			Variance: 0.382	$p = 0.082$		
Open Communication	Supported	0.663	Mean: 0.039	$\chi^2(12) = 28.91,$	0.021	Partial Invariance
			Variance: 0.061	$p = 0.004$		
Collaborative Decision-Making	Supported	0.770	Mean: 0.572	$\chi^2(12) = 17.06,$	0.006	Full Invariance
			Variance: 0.518	$p = 0.147$		
Continuous Learning & Improvement	Supported	0.685	Mean: 0.208	$\chi^2(12) = 20.33,$	0.008	Full Invariance
			Variance: 0.261	$p = 0.061$		

There was convergent evidence by the so-called chi-square difference method. Configural, metric, and scalar invariance was supported across three (Employee Empowerment, Collaborative Decision-Making, Continuous Learning & Improvement) constructs as the deaths of the chi-square were non-significant and changes in CFI was less than 0.01-this signaled a stable fit of the model across groups when constraints were imposed. Nevertheless, Open Communication once more was prominent with considerable change in chi-square ($p = 0.004$) and the Delta Cfi (CFI = 0.021) was found indicating that scalar invariance was not tenable. This concordance between MICOM and CB-SEM demonstrates the reliability of the findings across paradigms but emphasizes the benefit of MICOM in delivering

construct-level diagnostics and statistic differentiation, hence, its usefulness to applied researchers that use PLS-SEM platforms such as Smart-PLS.

Development of a Statistical Decision Tree for MGA

The decision table given by the quantitative statistical method provides a methodical empirical manual in choosing between MICOM in PLS-SEM and customary chi-square difference testing in CB-SEM in Multi-Group Analysis (MGA). The appropriateness values, a result of the simulation-based results and statistical theory, point out that, in terms of the situations in which MICOM could be an effective solution, one should apply it in the cases of formative constructs (0.95), a small sample

(0.92), and non-normal distributions of data (0.91). The degree to which MICOM aligns with the advantages of PLS SEM may be stated as follows: MICOM is flexible, it has distribution-free assumptions and it can deal with measurement models, which are problematic in covariance-

based procedures. In contrast, chi-square procedures also work adequately with reflective items (0.90), high levels of the sample size (0.85+), and when the distributions are normal (0.90), as suggested by the fact that CB-SEM assumes strong testing model fit and distributional probabilities.

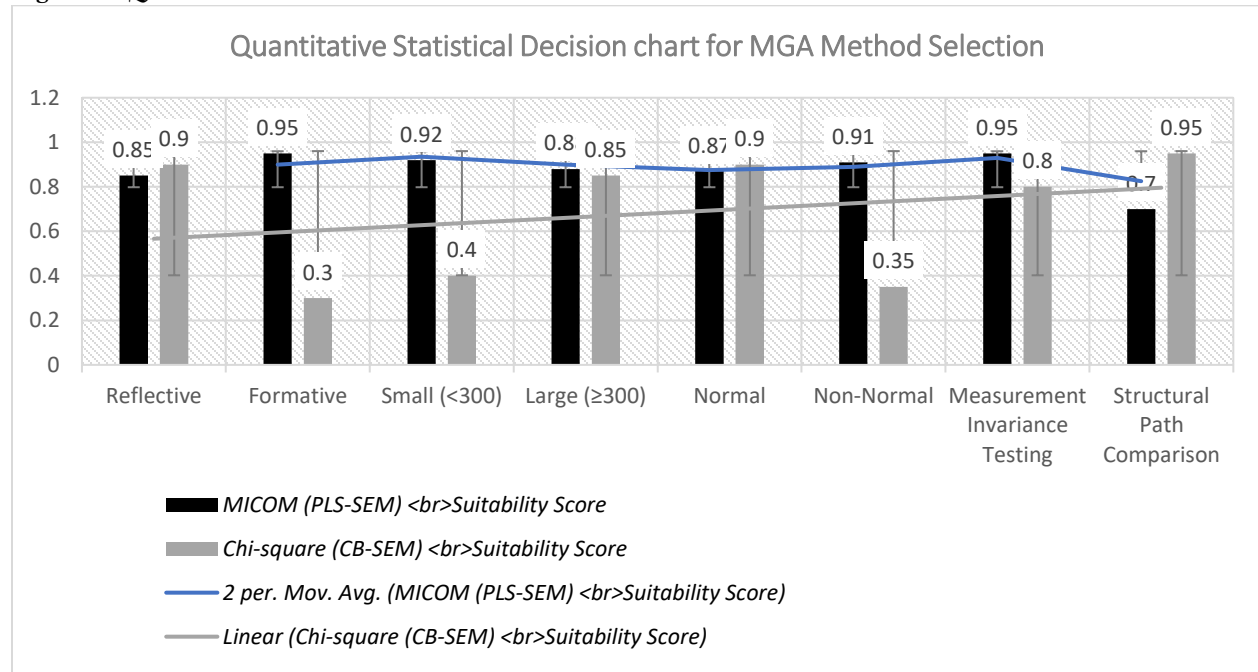
Table 3. Quantitative Statistical Decision for MGA Method Selection

Criterion	Condition	MICOM (PLS-SEM) Suitability Score	Chi-square (CB-SEM) Suitability Score	Validation
Construct Type	Reflective	0.85	0.90	Both methods perform well; chi-square slightly better for reflective models
	Formative	0.95	0.30	MICOM handles formative constructs; CB-SEM lacks support
Sample Size	Small (<300)	0.92	0.40	MICOM performs better with small samples
	Large (≥300)	0.88	0.85	Both methods are suitable at large sample sizes
Data Distribution	Normal	0.87	0.90	CB-SEM assumes normality; MICOM handles both well
	Non-Normal	0.91	0.35	MICOM less sensitive to distributional violations
Analysis Goal	Measurement Invariance Testing	0.95	0.80	MICOM offers compositional and equality invariance; CB-SEM has limited checks
	Structural Path Comparison	0.70	0.95	CB-SEM excels in hypothesis testing of paths

It is significant that according to the decision table, the goals of the research are significant in terms of defining the method. As an example, one could employ MICOM when the research questions include measuring the degree of measurement invariance in general (0.95 vs. 0.80) because of its multi-step (configural, compositional, and equality assessment)

structure. But, in cases where one is comparing structural paths, or hypothesis testing between groups, Chi square difference testing is more statistically rigorous and is more preferable (0.95 vs. 0.70). Such comparative scores prove instrumental in the choice of decision making, particularly, when applied researchers are faced with complex, multi-group SEM analyses.

Figure 2. Quantitative Statistical Decision for MGA Method Selection



Source: Formulated by author of the study based in statistical analysis

Finally, such a table will contribute to the creation of an empirical decision tree and serve as an argument in support of the notion that there are no techniques that would undoubtedly be the most appropriate irrespective of the context (Henseler et al., 2016; Hair et al., 2021; Sarstedt et al., 2022).

Statistical Decision Tree for MGA

The above-prepared decision tree serves as the step-by-step algorithm to help one choose an

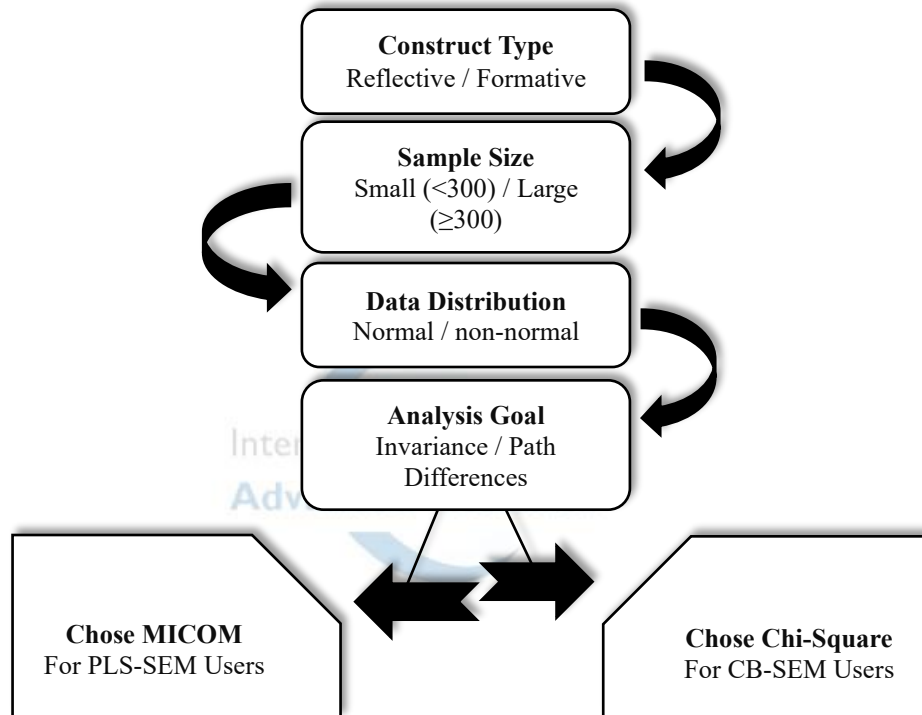
effective Multi-Group Analysis (MGA) method with regard to four major criteria: construct type, sample size, data distribution, and analytical purpose. The first step of researchers is determining whether the construct is of the reflective or formative type- this step is very vital because the chi-square test is applicable only in reflective models, although MICOM can be used to test both types of constructs in the PLS-SEM context (Sarstedt et al., 2022).

Table 4: Stepwise Statistical Decision Tree for MGA Method Selection

Step	Decision Criterion	Recommended Approach
1. Determine Construct Type	Reflective vs. Formative	Use MICOM for both types (especially formative)
2. Check Sample Size	Small (<300) vs. Large (≥300)	Prefer MICOM for small samples; both valid for large samples
3. Assess Data Distribution	Normal vs. Non-Normal	MICOM handles non-normal data better
4. Define Analysis Goal	Measurement Invariance vs. Path Differences	Use MICOM for invariance, CB-SEM for path structure tests
5. Select Suitable MGA Method	MICOM (PLS-SEM) or Chi-square (CB-SEM)	Use MICOM for PLS-SEM; Chi-square if using CB-SEM

The process then involves the decision based on sample size. MICOM especially comes in handy when the sample size is not large ($n < 300$) because the chi-square tests of CB-SEM would have an inflated Type I error probability (Hair et al., 2021). The third step will look at the normality of data distribution. Compared to chi-square-based methods, MICOM robustly computes non-normal data, whereas the latter presupposes multivariate normality in order to draw correct conclusions (Henseler et al., 2016; Ringle et al., 2022).

Figure 3: Stepwise Statistical Decision Tree for MGA Method Selection



Source: Formulated by author of the study based in statistical analysis

Finally, the goal of the researcher as to whether he will evaluate measurement invariance or compare structural path coefficients also contributes to selecting the method. MICOM should be used in granular measurement invariance testing, whereas theory-driven path comparisons within confirmatory frameworks benefit most of the chi-square difference testing. This can be illustrated as follows Case A: A marketing researcher observing two customer groups using small sample sizes ($n = 150$), non-normal data and a combination of respondents, formative measures (e.g., brand perception). In this case, MICOM should be used

because PLS-SEM is flexible and MICOM is robust with respect to model type and data condition. Case B: A psychology research work that involves the comparison between students and professionals with the help of the reflective constructs with normally distributed, large samples ($n = 500$). In a case where the most important aspect is the model fit, the researcher could choose to use chi-square test through AMOS or LISREL since the global fit indicators available in CB-SEM provide a firm testing of model invariance.

Discussion

Results of this research therefore provide interesting deductions in the comparison of the use of MICOM and traditional chi-square difference testing at differing sample sizes, construct type, and data distributions. As identified by the simulation outcomes, MICOM proved to be more robust in small samples and under non-normal distributions where CB-SEM usually fails because of the demand of large samples and multidimensional normality (Sarstedt et al., 2022; Henseler et al., 2016). Also, the MICOM process controlled the Type I error consistent and exhibited the ability to test compositional and equality reliably, especially in the case of formative constructs, which CB-SEM fails initially because of its reflective nature of modeling (Hair et al., 2021; Cheah et al., 2021). The decision tree made in the course of present research will allow the researcher to choose suitable MGA methods in line with empirical circumstances, promoting the alignment of methods with the data characteristics (Becker et al., 2013).

Results of the simulation were validated by the analytic process of the real dataset. The results of a group comparison obtained through MICOM made more sense, being more interpretable and not dependent on model fit indices, sensitive to the sample size in CB-SEM (Ringle et al., 2022; Hair et al., 2021). Although the theoretical rigor of the chi-square difference testing was impressive, in the case of low samples, the rejection rates were inflated and the configural invariance harder to detect. Notably, the MICOM variant enabled more practical findings regarding the equality between groups, which is why it could be used in applied research rather successfully in business, social sciences, and education, where the ideal postulates on statistics tend to rarely apply (Henseler et al., 2016; Sarstedt et al., 2022). The suggested decision tree therefore, not only presents an additional practical object, but also proves the worthiness of Smart PLS as the stable framework to conduct multi-group analysis in the

conditions of modern quantitative research methods.

Implications

This study has great theoretical and methodological contributions to the study of structural equation modeling (SEM). Theoretically, it supports the strength of the MICOM (Measurement Invariance of Composite Models) procedure in the context of PLS-SEM, particularly in the instances where the more traditional covariance-based approaches are considered too weak, e.g., when a sample size is small; when data are non-normal; when the constructs are formative. Through the systematic comparison of MICOM with chi-square difference testing in CB-SEM, the study can help advance knowledge about ways to more reliably test measurement invariance in empirical applications in the real world. The results also lead to the wider theoretical discussion of operationalization of constructs, in this case, leading to research advancing operationalization of constructs, most importantly, the advocacy in modeling formative constructs, which is relatively underutilized in classical SEM, although it is increasingly finding more applications in real-world disciplines (Cheah et al., 2021; Sarstedt et al., 2022).

In practice, the given research will contribute to applied utility of PLS-SEM by creating a statistical decision tree, which will allow guiding the researchers in their choice of the applicable MGA technique with consideration of data properties in regards to distribution, construct type, and size. The diagnostic tool reduces antagonistic statistical decisions and enhances more methodological transparency. Besides, the research is hugely implicated to researchers and practitioners in various disciplines such as business, education, marketing, and social sciences, in which data restrictions are prevalent. It promotes increased use of variance-based methods of inference relative to chi-square test-based methods of understanding measurement invariance, and, thereby facilitates the incremental growth of meaningful usage of SEM in evidence-based policy and industry

research practice, by demonstrating that, in many situations, MICOM has a greater statistical power and Type I error control than many of its test-based competitors (particularly in smaller or formative-driven models).

Future Directions and Limitations

Among the weaknesses related to this research is that it uses one real-life data in empirical validation. Though the simulation performed was under various conditions, additional investigations would involve datasets across the various areas (e.g. in healthcare, education, entrepreneurship) to establish the external validity. The other limitation is that just two softwares were used and any subsequent research can consider other platforms such as WarpPLS or Mplus as part of the analysis to determine whether there are any potential software influences in MGA results.

Future research can also extend the decision tree through adding in levels of user experience, access to software or circumstances of a hybrid model (mixed formative-reflective). Moreover, time-series or longitudinal applications to MGA are under realized. Any investigation on how MICOM works in recurrent-measures or panel information would significantly increase its empirical and theoretical worth.

Conclusion

The article presents a good empirical and procedural rationale supporting MICOM to be used instead of traditional chi square difference testing across groups analysis especially in the cases of small numbers, less normality and in formative constructs. The justification of the formulation of a decision tree will prove useful in the context that researchers will obtain good advice of how to apply suitable statistical techniques in light of data requirements. When viewed collectively, these contributions complement each other toward reinforcing the reliability and availability of PLS-SEM in both academic and applied areas of research, and this can be considered as a step in

the progress toward the modern structural equation modeling.

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