Chapter 12

Mplus Jamovi Amos and Spss Programs in Partial Mediation Model: A Simulation Study

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Abstract

This study aims to investigate the performance of Mplus, Jamovi, Amos and Spss programs, which are widely used for partial mediation model, with a certain sample size and categorical data. In line with the purpose of the study, R program was used to generate data for partial mediation model. The three path coefficients of the model are pre-assigned as real values with a 0.6, b 0.7 and c path 0.3 and there is no other pre-assigned value. Sample size selection is 100, 200, 300, 400 and 500 units. In the established model, X latent variable has 4, M latent variable has 3 and Y latent variable has 5 observed variables. All observed variables have 5-categorical structure. The model was analyzed in all programs; direct effects, indirect effects and fit values were obtained. The estimation techniques of the programs are WLSMV, DWLS, ML and OLS, respectively. The closeness of the programs to the previously assigned values as performance criteria was intended to be examined. For this situation, Mean Absolute Bias- MAB and Relative Bias- RB values were used. The findings obtained were as follows. In all programs, the direct effect from the latent variable X to the latent variable Y was found to be insignificant in sample sizes of 100 and 200 units, and all other path coefficients were found to be significant. In this case, the existing partial mediation model was transformed into a full mediation model. This result indicates that the sample size of 100 and 200 units is insufficient for model studies on partial mediation relationship. While all programs had overestimation in the sample size of 100 units, underestimation was obtained in sample sizes increasing with 200 units. All programs had quite good fit values in all volumes. According to MAB and RB values, Spss indicates that its use for categorical data is problematic with its quite high deviation results. In other programs, MAB and RB values of 300 units sample were found to be good and the best performance was provided by Mplus program with WLSMV estimation technique. The next performance ranking after Mplus program was Jamovi and Amos.

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INTRODUCTION

Structural equation modeling (SEM) has a historical background with the assumption of linearity (Bollen 1989) that addresses the relationships between latent variables through observed variables. This assumption of linearity has been included in many packaged programs. However, this limitation is not sufficiently appropriate in the branches of science where SEM is frequently used (Lee and Zhu, 2000; Wall and Amemiya, 2007; Wall, 2009). Because researchers in the fields of psychometrics, education and marketing generally address the quadratic variables of latent variables (Arminger and Muthen, 1998).

When the hypotheses of solid theories are examined, we see that latent variables point to interaction and quadratic variables. For example, in psychology, the theory of reasoned action, expectancy-value attitude theory or an extension of the theory of planned behavior can be given. We see another example in educational sciences. Ganzach (1997) stated that children's expectations from education depend on the nonlinear relationships between their parents' level of education (Lee and Zhu, 2000; Moosbrugger et al., 2009). Many theories in social and behavioral sciences have nonlinear relationships of latent variables (Kelava and Brandt, 2009; Kelava and Nagengast, 2012).

Therefore, expanding the linearity restriction by adding nonlinear relationships of latent variables to SEM studies will allow the creation of strong theories by estimating robust hypotheses (Wall and Amemiya, 2007).

Recent studies have determined that adding nonlinear relationships of latent variables to the model provides better causality (Lee and Song, 2003). More than one model type has been defined for nonlinear structure types and more than one estimation technique has been developed for them. In this way, a rapidly growing literature has emerged in this field (Wall and Amemiya, 2007).

Model studies addressing the interaction effects of latent variables have become important statistical tools in many branches of science. Studies in psychology and behavioral sciences increasingly address the mediation and moderation effects of independent variables in order to better reveal causality on independent variables (Çağlayan and Özenç, 2024; Hayes, 2018).

In a content study conducted in educational sciences in the national literature, it was determined that 74% of the theses conducted between 2004 and 2023 were single mediation models. This difference seen in mediation analysis studies was effective in determining the model in the current study.

Mostly ready-made scales or partially developed scales were used as data collection tools for mediation analysis (Çağlayan and Özenç, 2024). The data obtained through scales are in the type of ordinal categorical data and there are multiple estimation techniques for their evaluation in frequentist statistics. These techniques are recommended as Unweighted Least Square (ULS) and Diagonally Weighted Least Square (DWLS). When there is continuous data and the data assumes normality, the most commonly used method is the Maximum Likelihood (ML) method (Jöreskog, 1969; Maydeu-Olivares, 2017; Shi et al., 2018; Shi and Maydeu-Olivares, 2020).

It is observed that in model studies in social and behavioral sciences, ordinal categorical data is frequently used and researchers also frequently use the ML method as a estimation technique. However, it is quite difficult to ensure normality in data belonging to ordinal variables. Different techniques developed under these conditions need to be used. Since the model will only calculate the indirect effect with the mediation model, the performance of these techniques should be examined even if the data is normally distributed (Yang-Wallentin et al., 2010).

The present study aims to measure the performance of Mplus, Jamovi, Amos and Spss package programs, which are frequently used in simple mediation models. Considering that researchers are not conscious about choosing the estimation technique, the default estimation techniques given directly for each program are WLSMV (Weighted least squares mean and variance-corrected weighted least squares), DWLS, ML and OLS (Ordinary least squares), respectively. The given estimation techniques were evaluated by considering biases from the perspective of sample size.

MATERIAL AND METHODS

Material

The model established in the study is a simple/partial mediation model, and the number of categories, the selection of the number of observed variables, the sample size, and the prior assignment of values for the path coefficients were determined by using similar studies in the literature (e.g., Forero and Maydeu-Olivares, 2009; Li, 2021; Yang-Wallentin et al., 2010). The model of the study is shown in Figure 1.

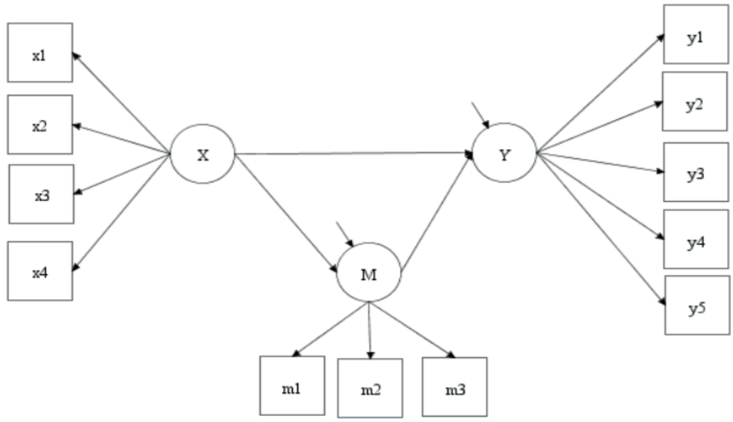


Figure 1. Path Diagram of the model

In the model, the path coefficients were previously assigned from X to Y as 0.3, from X to M as 0.6, and from M to Y as 0.7. With this assignment, the indirect effect was obtained as 0.42. No assignment was made for factor loadings. The number of categories was determined as five. The sample size was determined as 100, 200, 300, 400, and 500 units.

Methods

The Collection of the Data

The data generation process was carried out by taking into account the entire sample volume and the previously assigned values of the model via the R program. After the data were generated continuously in the R program, they were converted into five-category data.

Statistical Analysis

The techniques used by the estimation methods determined for mediation analysis in calculating the indirect effect are as follows. While WLSMV and DWLS estimation techniques use the Delta method, ML and OLS use the Bootstrapping method. This selection process is again the method that the existing package programs assign the estimation technique by default.

In measuring the performances of WLSMV, DWLS, ML and OLS estimation techniques, the closeness of the path coefficient values to the previously assigned values was examined from the perspective of the sample size. In measuring the closeness, mean absolute bias (MAB) and relative bias (RB) values were examined. For the evaluation of information where biases are considered, based on previous simulation studies (Curran et al., 1996; Bandalos, 2002; Flora and Curran, 2004; Kaplan, 1989; Yang-Wallentin et al., 2010), it was considered that a relative bias of less than 5% is insignificant, a bias between 5-10% indicates a moderate level of bias, and a bias greater than 10% indicates a significant bias. Since the true value and the estimated value will be compared in all program findings, the unstandardized coefficients are taken into account and included in the tables. However, the standardized coefficients are included in the path diagram according to the sample size of the model.

RESULTS

The data generation process for the simulation study was successfully achieved for all sample sizes in the R program. In the current order, analyses were performed for all sample sizes for the model in all programs and the findings were determined. The outputs of Mplus, Jamovi, Amos and Spss, as well as the outputs of MAB and RB, will be given in this section. First, the outputs of the Mplus program were obtained as follows.

Outputs of the Mplus Program

The analysis findings starting from a sample size of 100 units up to 500 units are as follows.

Table 1. Mplus sample size 100

Sample	**Estimator**	**Path Coefficient :True Value**	**Estimated Value (S.E)**	**p Value (%2.5 Low- %2.5Upper Limit)**	**Difference**
100	WLSMV	X -> M: 0.6	0.759 (0.159)	0.000 (0495- 1.125)	0.159
100	WLSMV	M -> Y: 0.7	0.761 (0.191)	0.000 (0.467- 0.196)	0.061
100	WLSMV	X -> Y: 0.3	0.033 (0.222)	0.882 (-0.452- 0.389)	-0.267
100	WLSMV	X-> M -> Y: 0.42	0.578 (0.222)	0.009 (0.307- 1.131)	0.158
Model Fit	**CFI**	**TLI**	**SRMR**	**RMSEA(%90 CI and RMSEA Probability<=.05)**	**χ^2/sd (p value)**
	1.000	1.016	0.037	0.000 (0.000- 0.041 and 0.975)	41.804/51 (0.8172)

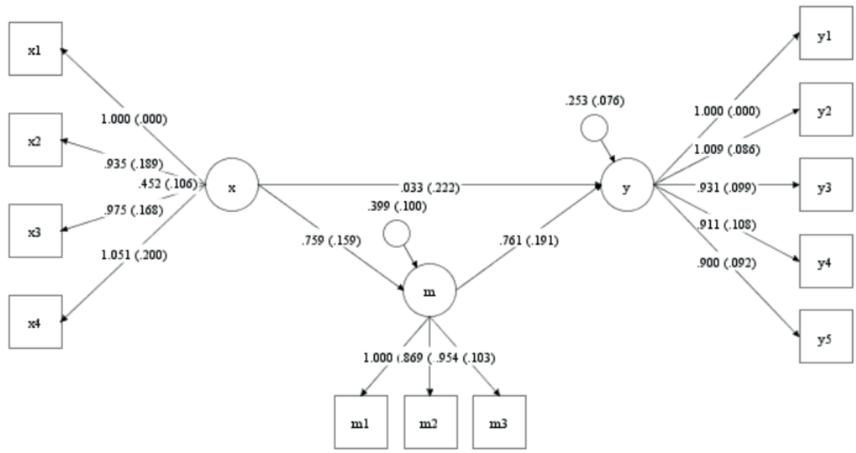


Figure 2. Mplus path diagram N= 100

It is seen that the model fit values are quite good (Schermelleh-Engel et al., 2003). When the path coefficients considered in the study are examined, it is seen that all paths are significant except the direct effect of X on Y. This situation transforms the model from a partial mediation model to a full mediation model. In this case, the sample size of 100 units is not sufficient for the partial mediation model. In addition, overestimation is observed in all paths except the direct effect of X on Y.

Table 2. Mplus sample size 200

Sample	**Estimator**	**Path Coefficient :True Value**	**Estimated Value (S.E)**	**p Value (%2.5 Low- %2.5Upper Limit)**	**Difference**
200	WLSMV	X -> M: 0.6	0.509 (0.085)	0.000 (0.351- 0.685)	-0.091
200	WLSMV	M -> Y: 0.7	0.776 (0.121)	0.000 (0.562- 1.040)	0.076
200	WLSMV	X -> Y: 0.3	0.045 (0.105)	0.666 (-0.168- 0.245)	-0.255
200	WLSMV	X-> M -> Y: 0.42	0.394 (0.087)	0.000 (0.252- 0.590)	-0.026
Model Fit	**CFI**	**TLI**	**SRMR**	**RMSEA(%90 CI and RMSEA Probability<=.05)**	**χ^2/sd (p value)**
	1.000	1.004	0.030	0.000 (0.000- 0.038 and 0.992)	46.283/51 (0.6612)

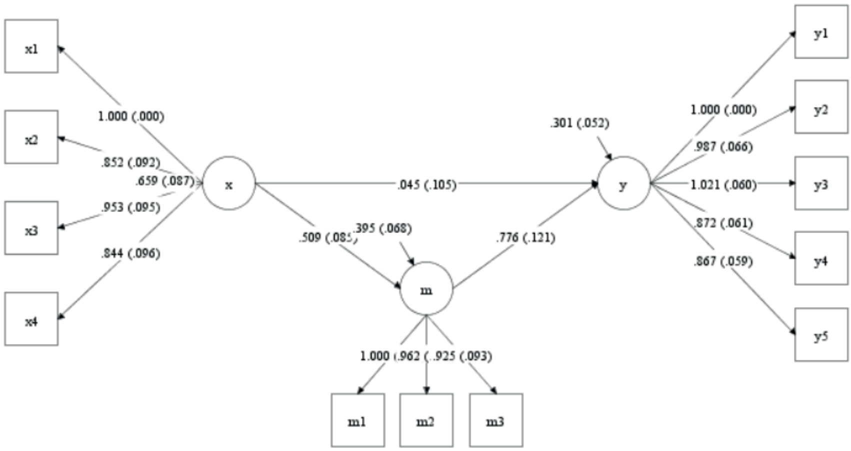


Figure 3. Mplus path diagram N= 200

At 200 units, model fit values were again obtained quite well, while the direct effect of X on Y was obtained as insignificant. In this case, as in the 100-unit sample size, the model has moved from a partial mediation model to a full mediation model. We can say that the partial mediation model is not sufficient at 200 units. In addition, instead of an overestimation as in 100 units, there is underestimation at this volume, except for the direct effect of M on Y.

Table 3. Mplus sample size 300

Sample	**Estimator**	**Path Coefficient :True Value**	**Estimated Value (S.E)**	**p Value (%2.5 Low- %2.5Upper Limit)**	**Difference**
300	WLSMV	X -> M: 0.6	0.550 (0.095)	0.000 (0.378- 0.755)	-0.05
300	WLSMV	M -> Y: 0.7	0.671 (0.085)	0.000 (0.506- 0.841)	-0.029
300	WLSMV	X -> Y: 0.3	0.282 (0.091)	0.002 (0.107- 0.466)	-0.018
300	WLSMV	X-> M -> Y: 0.42	0.369 (0.074)	0.000 (0.244- 0.537)	-0.051
Model Fit	**CFI**	**TLI**	**SRMR**	**RMSEA(%90 CI and RMSEA Probability<=.05)**	**χ^2/sd (p value)**
	1.000	1.007	0.021	0.000 (0.000- 0.016 and 1.000)	38.324/51 (0.9049)

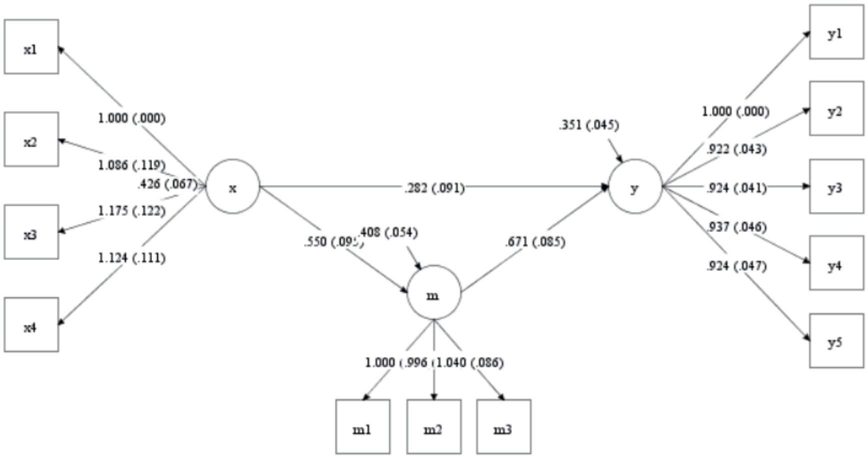


Figure 4. Mplus path diagram N= 300

It is seen that there is a significant difference except for the linear effect of X on Y at 300 units (p>0.001) and the model fit values are quite good. Underestimation was observed in all path coefficients. We can say that a sample size of 300 units shows a borderline adequacy for the partial mediation model.

Table 4. Mplus sample size 400

Sample	**Estimator**	**Path Coefficient :True Value**	**Estimated Value (S.E)**	**p Value (%2.5 Low- %2.5Upper Limit)**	**Difference**
400	WLSMV	X -> M: 0.6	0.566 (0.086)	0.000 (0.411- 0.750)	-0.034
400	WLSMV	M -> Y: 0.7	0.534 (0.061)	0.000 (0.422- 0.665)	-0.166
400	WLSMV	X -> Y: 0.3	0.284 (0.069)	0.000 (0.148- 0.419)	-0.016
400	WLSMV	X-> M -> Y: 0.42	0.303 (0.055)	0.000 (0.209- 0.424)	-0.117
Model Fit	**CFI**	**TLI**	**SRMR**	**RMSEA(%90 CI and RMSEA Probability<=.05)**	**χ^2/sd (p value)**
	0.998	0.998	0.023	0.017 (0.000- 0.037 and 0.999)	56.904/51 (0.2647)

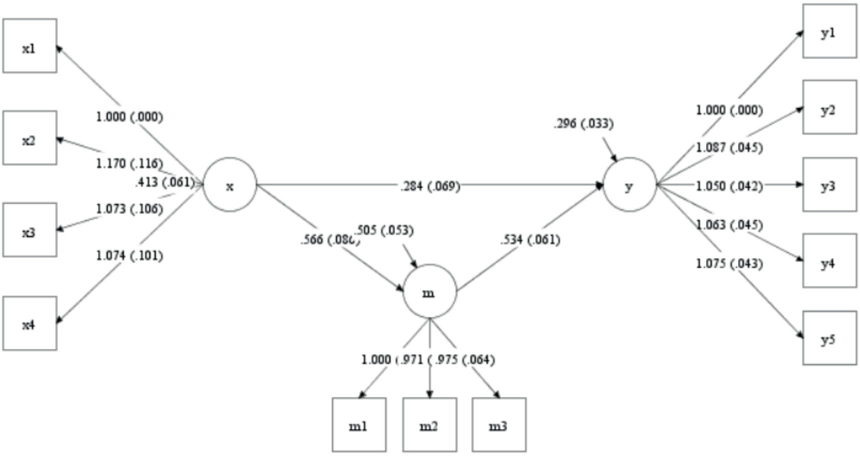


Figure 5. Mplus path diagram N= 400

It is seen that all path coefficients of the model are significant at 400 units. The fit values are at a level that can be seen as a result of using real data sets. In addition, there is underestimation.

Table 5. Mplus sample size 500

Sample	Estimator	Path Coefficient :True Value	Estimated Value (S.E)	p Value (%2.5 Low- %2.5Upper Limit)	Difference
500	WLSMV	X -> M: 0.6	0.565 (0.059)	0.000 (0.457- 0.685)	-0.035
500	WLSMV	M -> Y: 0.7	0.576 (0.078)	0.000 (0.427- 0.737)	-0.124
500	WLSMV	X -> Y: 0.3	0.265 (0.072)	0.000 (0.121- 0.410)	-0.035
500	WLSMV	X-> M -> Y: 0.42	0.325 (0.050)	0.000 (0.236- 0.432)	-0.095
Model Fit	**CFI**	**TLI**	**SRMR**	**RMSEA(%90 CI and RMSEA Probability<=.05)**	**χ^2/sd (p value)**
	0.996	0.994	0.022	0.028 (0.008- 0.042 and 0.996)	70.625/51 (0.0357)

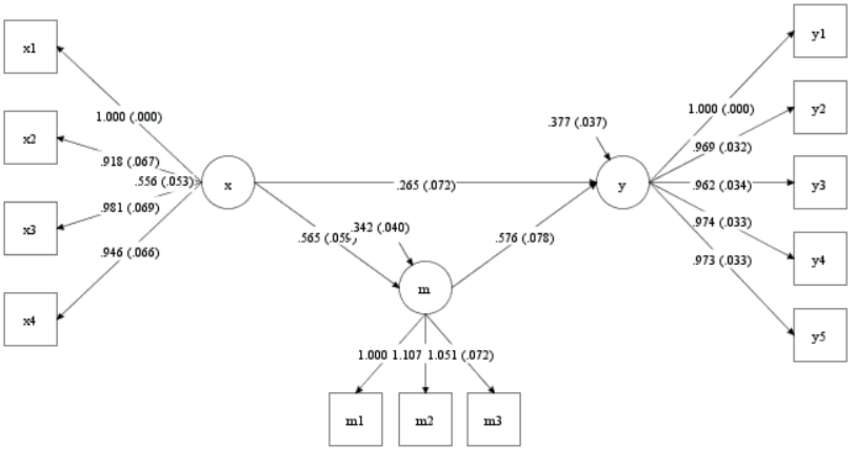


Figure 6. Mplus path diagram N= 500

At 500 units, the path coefficients were again found to be significant, but while the underestimation continued, a decrease in this value was observed with the increase in the sample size. In addition, an increase in the χ^2 value from the fit values was clearly observed with the increase in the sample size and had the highest value at 500 units. The R program was used for the visuals of the MAB and RB values to determine the closeness between the estimated values obtained from the program and the real values. The findings regarding the sample sizes are given in Figures 7 and 8.

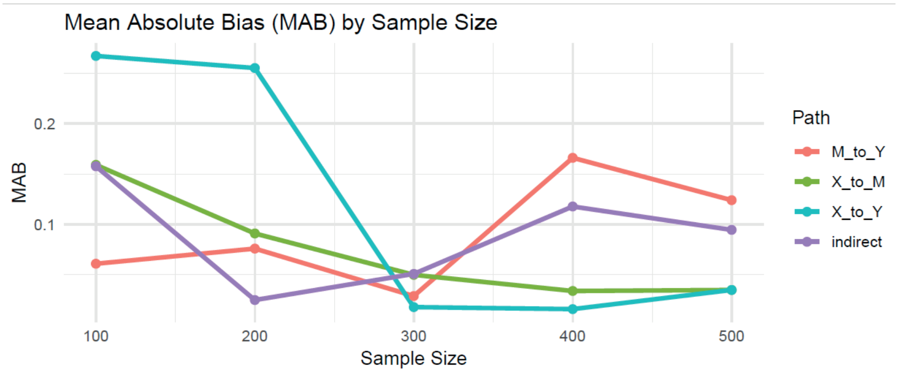
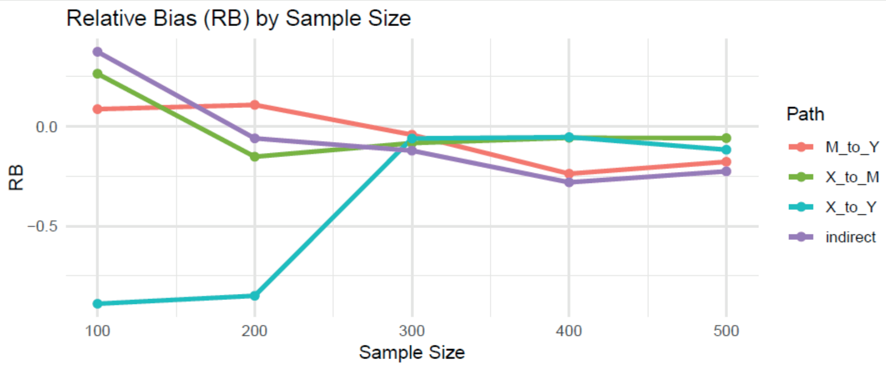


Figure 7. Mplus MAB value



Figüre 8. Mplus RB value

When the MAB and RB graphs are examined, while there is a very good result in the 300-unit sample size, this situation did not improve as the sample size increased. We can state that the lowest bias values were observed in 300 units. While the RB values in 400 and 500 units again indicate low, insignificant bias, this situation resulted in a greater deviation in the MAB values.

Outputs of the Jamovi Program

The Jamovi program uses the DWLS estimation technique for the model with the semLJ module and the Delta method for calculating indirect effects. The estimation technique selection process is generally specified in this program as in the Mplus program with the use of ordered categorical data in programs. In addition, although the Jamovi program allows for the selection of more than one estimation technique, for example, instead of the WLSMV method that was tried to be selected for this model, the DWLS technique was used. The findings obtained for all sample sizes were as follows.

Table 6. Jamovi sample size 100

Sample	**Estimator**	**Path Coefficient :True Value**	**Estimated Value (S.E)**	**p Value (Low-Upper Limit)**	**Difference**
100	DWLS	X -> M: 0.6	0.7594 (0.1311)	<.001 (0.503-1.016)	0.1594
100	DWLS	M -> Y: 0.7	0.7609 (0.159)	<.001 (0.450-1.072)	0.0609
100	DWLS	X -> Y: 0.3	0.0328 (0.174)	0.850 (-0.308-0.373)	-0.2672
100	DWLS	X-> M -> Y: 0.42	0.578 (0.164)	<.001 (0.257-0.899)	0.158
Model Fit	**Scaled CFI**	**Scaled TLI**	**Scaled SRMR**	**Scaled RMSEA(p value)**	**χ^2/sd (p value)**
	1.000	1.025	0.037	0.000 (0.976)	41.5/51 (0.825)

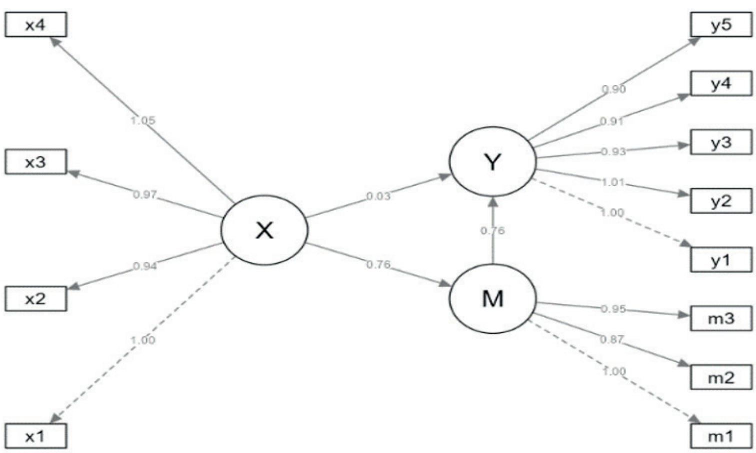


Figure 9. Jamovi path diagram N=100

Except for the path coefficient of X on Y in 100 units, all other paths are both significant and overestimated. Model fit values are quite good (Schermelleh-Engel et al., 2003). With the direct effect being insignificant, the partial mediation model turns into a full mediation model. In this case, it is said that a sample size of 100 units will not be sufficient for a partial mediation model. In addition, the outputs of the Mplus program in 100 units and the outputs of Jamovi gave very close values.

Table 7. Jamovi sample size 200

Sample	Estimator	Path Coefficient :True Value	Estimated Value (S.E)	p Value (Low-Upper Limit)	Difference
200	DWLS	X -> M: 0.6	0.5085(0.0798)	< .001 (0.352-0.665)	-0.0915
200	DWLS	M -> Y: 0.7	0.7755 (0.1140)	<.001 (0.552-0.999)	0.07555
200	DWLS	X -> Y: 0.3	0.0452 (0.1002)	0.652 (-0.151-0.242)	-0.2548
200	DWLS	X-> M -> Y: 0.42	0.394 (0.084)	<.001 (0.230-0.558)	-0.026
Model Fit	**Scaled CFI**	**Scaled TLI**	**Scaled SRMR**	**Scaled RMSEA(p value)**	**χ^2/sd (p value)**
	1.000	1.004	0.030	0.000 (0.992)	46.1/51 (0.668)

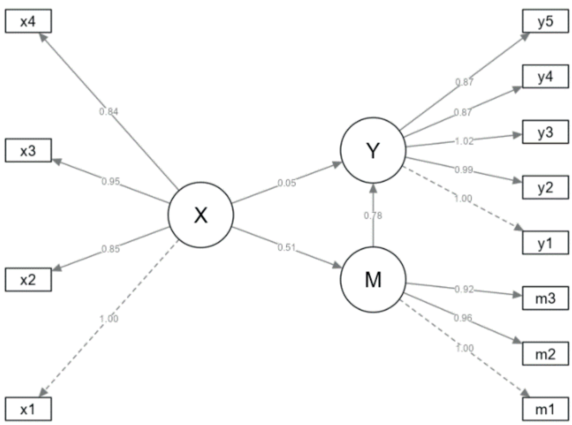


Figure 10. Jamovi path diagram N=200

The direct effect of X on Y in 200 units is also obtained with insignificant and incomplete estimation. This situation transforms the partial mediation model into full mediation. It is seen that the other path coefficients are significant. There is an increase in the χ^2 value from the model fit values. It cannot be said that 200 units are sufficient for the partial mediation model.

Table 8. Jamovi sample size 300

Sample	Estimator	Path Coefficient :True Value	Estimated Value (S.E)	p Value (Low- Upper Limit)	Difference
300	DWLS	X -> M: 0.6	0.550 (0.0899)	<.001 (0.374- 0.727)	-0.05
300	DWLS	M -> Y: 0.7	0.671 (0.0844)	<.001 (0.506- 0.837)	-0.029
300	DWLS	X -> Y: 0.3	0.282 (0.0877)	0.001 (0.110- 0.454)	-0.018
300	DWLS	X-> M -> Y: 0.42	0.369 (0.070)	<.001 (0.231- 0.507)	-0.051
Model Fit	**Scaled CFI**	**Scaled TLI**	**Scaled SRMR**	**Scaled RMSEA(p value)**	**χ^2/sd (p value)**
	1.000	1.007	0.021	0.000 (1.000)	38.2/51 (0.907)

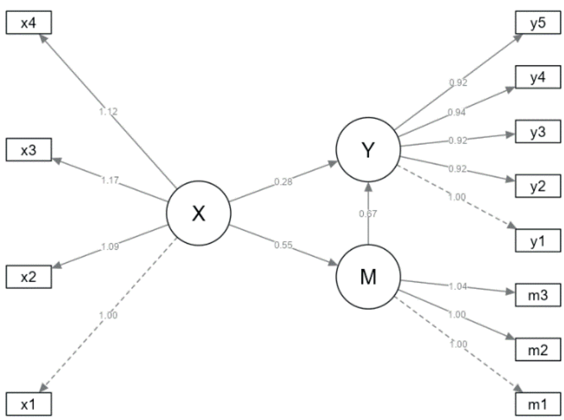


Figure 11. Jamovi path diagram N=300

In the 300-unit sample size, all path coefficients of the model were obtained with significant and incomplete estimation. A decrease is observed in the χ^2 value of the model fit values. When all data are evaluated, it can be said that the model's prediction and fit values are good, together with the closeness to the previously assigned values. This situation suggests that it will be improved even more as the sample size increases, due to the asymptotic theory.

Table 9. Jamovi sample size 400

Sample	Estimator	Path Coefficient :True Value	Estimated Value (S.E)	p Value (Low-Upper Limit)	Difference
400	DWLS	X -> M: 0.6	0.566 (0.0803)	<.001 (0.409-0.724)	-0.034
400	DWLS	M -> Y: 0.7	0.534 (0.0604)	<.001 (0.416-0.652)	-0.166
400	DWLS	X -> Y: 0.3	0.284 (0.0691)	<.001 (0.149-0.420)	-0.016
400	DWLS	X-> M -> Y: 0.42	0.303 (0.053)	<.001 (0.199-0.406)	-0.117
Model Fit	**Scaled CFI**	**Scaled TLI**	**Scaled SRMR**	**Scaled RMSEA(p value)**	**χ^2/sd (p value)**
	1.000	1.004	0.023	0.017 (0.999)	56.8/51 (0.268)

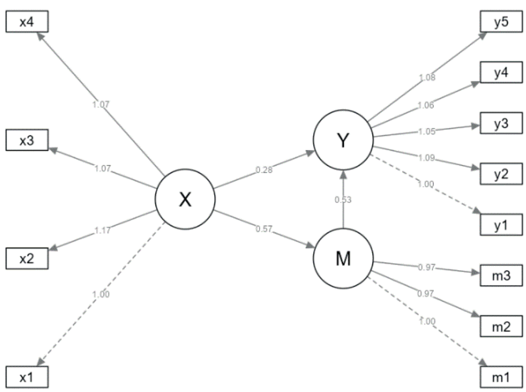


Figure 12. Jamovi path diagram N=400

All path coefficients are significant and underestimation is observed in all of them in 400 units. In addition, there is a decrease in model fit values. This situation may actually be due to the extremely good fit values in 300 units. Because the fit values in 400 units are actually seen as the highest fit values that can be made with real data sets. In this case, the decrease in model fit values actually seems reasonable.

Table 10. Jamovi sample size 500

Sample	**Estimator**	**Path Coefficient :True Value**	**Estimated Value (S.E)**	**p Value (Low- Upper Limit)**	**Difference**
500	DWLS	X -> M: 0.6	0.565 (0.0581)	<.001 (0.451- 0.679)	-0.035
500	DWLS	M -> Y: 0.7	0.576 (0.0744)	<.001 (0.430- 0.722)	-0.124
500	DWLS	X -> Y: 0.3	0.265 (0.0699)	<.001 (0.128- 0.402)	-0.035
500	DWLS	X-> M -> Y: 0.42	0.325 (0.049)	<.001 (0.230- 0.421)	-0.095
Model Fit	**Scaled CFI**	**Scaled TLI**	**Scaled SRMR**	**Scaled RMSEA(p value)**	**χ^2/sd (p value)**
	1.000	1.002	0.022	0.028 (0.996)	70.5/51 (0.037)

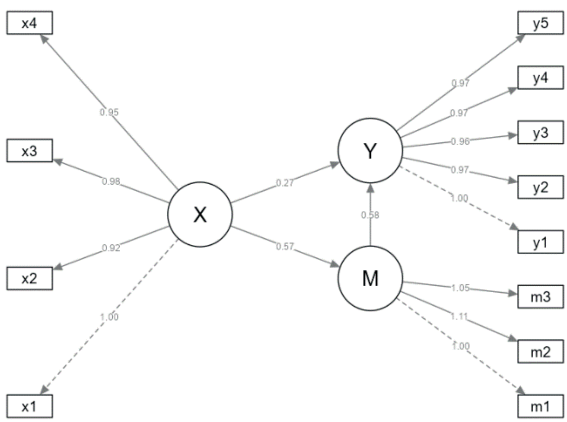


Figure 13. Jamovi path diagram N=500

All paths are significant and all have underestimation at 500 units. An increase in the χ^2 value from the model fit values occurred at this volume with 300 units. Model improvements do not occur after 300 units with the use of simulation data. This situation may be due to randomly obtained data. This situation can actually be clarified with real data sets. However, the Jamovi program, like the Mplus program, made its best estimates at 300 units.

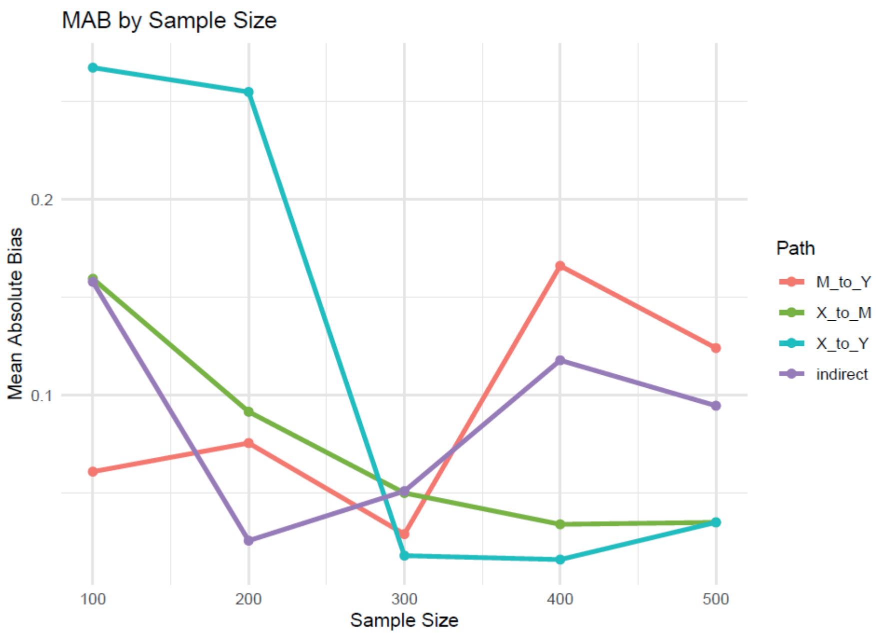


Figure 14. Jamovi MAB value

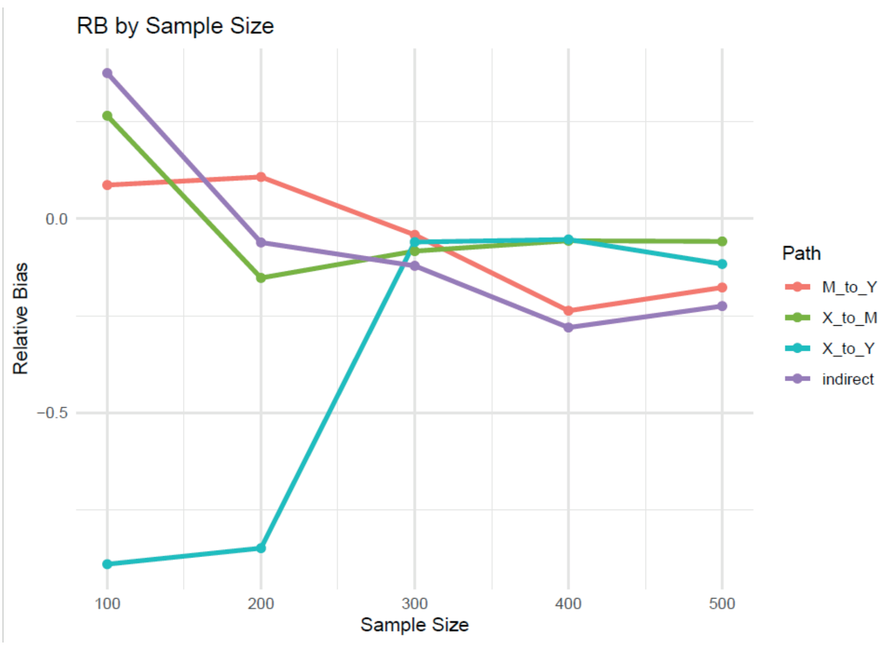


Figure 15. Jamovi RB value

As in the Mplus program, it is seen that the least bias values are obtained in the Jamovi program at 300 units. There are deteriorations at 400 and 500 units, but there is still a relative bias of less than 5%. This is an insignificant bias according to the threshold values specified in the literature. However, due to the asymptotic theory, further improvements were expected, but this did not happen. Although the MAB values also showed an increase at 400 and 500 units, even this increase did not approach the maximum value of 2%. In fact, everything seems to be fine at 300 units and above. However, it does not happen exactly as expected.

Outputs of the Amos Program

This program, which is frequently used by many application researchers in SEM studies, uses the ML estimation technique by default. This technique, which works with continuous data and multivariate normality assumption, is unfortunately also frequently used with categorical data. Although the Amos program allows selection in the case of categorical data, this situation is seen as a very technical issue for application researchers. Due to this situation, the partial mediation relationship was examined with the Amos program using the ML estimation technique. In fact, the use of the ULS technique is what should have been done, but since application researchers continued with the default estimation technique, ML was selected in the estimation of the model. This selection reflects the purpose of the study. Because with this research, it was aimed to carry out a study that could be an example for application researchers by not intensively addressing estimation techniques and theoretical knowledge. The findings obtained are as follows:

Table 11. Amos sample size 100

Sample	**Estimator**	**Path Coefficient :True Value**	**Estimated Value (S.E)**	**p Value (Low-Upper Limit)**	**Difference**	**CFI**	**TLI**	**RMSEA**	**χ^2/sd**
100	ML	X -> M: 0.6	0.720 (0.185)	***	0.120	1.000	1.008	0.000	0.952
100	ML	M -> Y: 0.7	0.770 (0.185)	***	0.07				
100	ML	X -> Y: 0.3	0.076 (0.185)	0.68	-0.224				
100	ML	X-> M -> Y: 0.42	0.555 (0.207)	(0.288-1.088)	0.135				

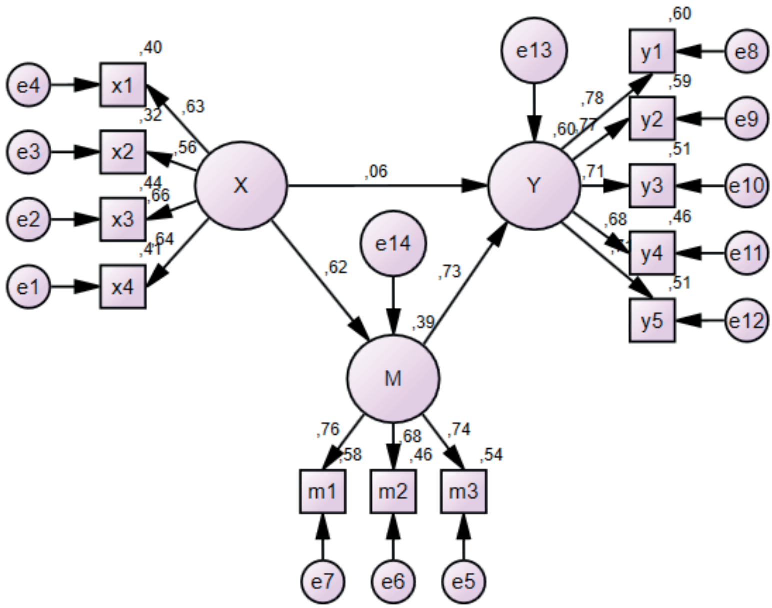


Figure 16. Amos path diagram N=100

The evaluation in 100 units is quite similar to those in the Mplus and Jamovi programs. In this program, the direct effect of X on Y was found insignificant and the model changed from partial mediation to full mediation. In this case, it actually says that many other issues should not be considered. Because the assumed model structure has changed and the interpretation and explanation of the relationships established in the literature have become quite difficult. However, the model fit values are quite good as in other programs (Schermelleh-Engel et al., 2003). The direct effect of X on Y was obtained as 0.033 (0.222), 0.0328 (0.174), 0.076 (0.185) in the models, respectively. An overestimation is observed in the ML and Amos programs. In the current situation, we can say that the WLSMV and DWLS techniques, which are suitable techniques for categorical data, make less estimates than the ML used for continuous variables.

Table 12. Amos sample size 200

Sample	Estimator	Path Coefficient :True Value	Estimated Value (S.E)	p Value (Low-Upper Limit)	Difference	CFI	TLI	RMSEA	χ^2/sd
200	ML	X -> M: 0.6	0.549 (0.108)	***	-0.051	1.000	1.011	0.000	0.856
200	ML	M -> Y: 0.7	0.840 (0.148)	***	0.140				
200	ML	X -> Y: 0.3	0.047 (0.112)	0.674	-0.253				
200	ML	X-> M -> Y: 0.42	0.461 (0.116)	(0.277-0.725)	0.041				

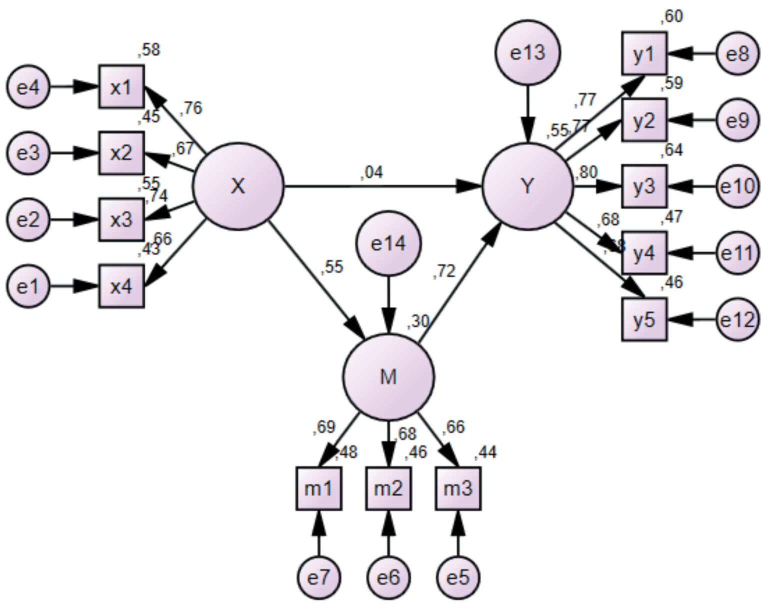


Figure 17. Amos path diagram N=200

At 200 units, it has the same results as the first two programs. The effect of X on Y was insignificant. Underestimation started again after 100 units. The model fit values are quite good.

Table 13. Amos sample size 300

Sample	Estimator	Path Coefficient :True Value	Estimated Value (S.E)	p Value (Low-Upper Limit)	Difference	CFI	TLI	RMSEA	χ^2/sd
300	ML	X -> M: 0.6	0.497 (0.085)	***	-0.103	1.000	1.003	0.000	0.934
300	ML	M -> Y: 0.7	0.663 (0.097)	***	-0.037				
300	ML	X -> Y: 0.3	0.241 (0.084)	0.004	-0.059				
300	ML	X-> M -> Y: 0.42	0.330 (0.062)	(0.222-0.466)	-0.09				

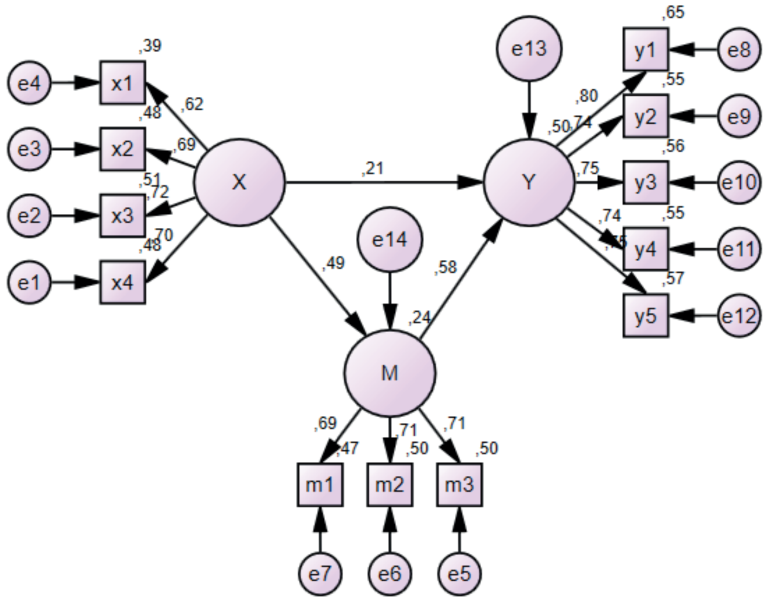


Figure 18. Amos path diagram N=300

The direct effect of X on Y is p>0.001 and is significant for 5% and 0.1%. We see a result close to this situation in the best Mplus program and the next closest result in the Jamovi program outputs. All path coefficients are significant and underestimation is observed in all of them. The fit values are again quite good.

Table 14. Amos sample size 400

Sample	Estimator	Path Coefficient :True Value	Estimated Value (S.E)	p Value (Low-Upper Limit)	Difference	CFI	TLI	RMSEA	χ^2/sd
400	ML	X -> M: 0.6	0.522 (0.83)	***	-0.048	0.992	0.990	0.027	1.282
400	ML	M -> Y: 0.7	0.545 (0.069)	***	-0.155				
400	ML	X -> Y: 0.3	0.266 (0.072)	***	-0.034				
400	ML	X-> M -> Y: 0.42	0.282 (0.054)	(0.191-0.400)	-0.138				

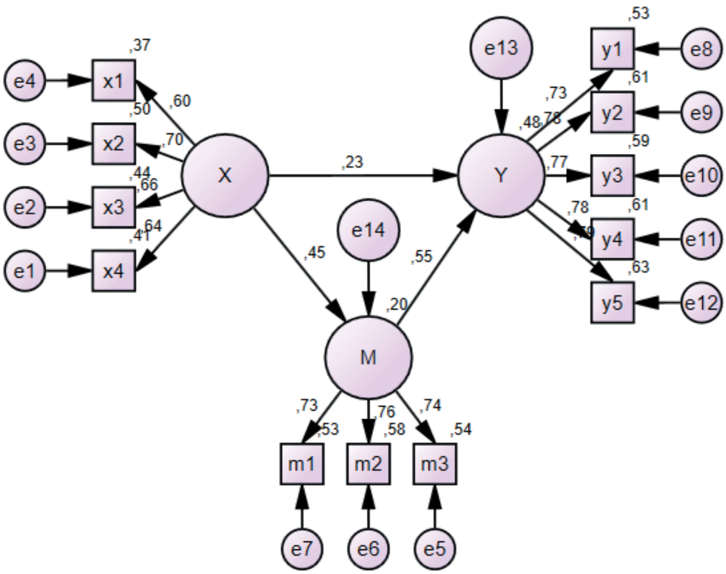


Figure 19. Amos path diagram N=400

Model fit values at 400 units are seen to have turned into the best fit values with real data. However, the proximity to real values is still not at the desired level. This situation is similar to other program outputs.

Table 15. Amos sample size 500

Sample	Estimator	Path Coefficient :True Value	Estimated Value (S.E)	p Value (Low-Upper Limit)	Difference	CFI	TLI	RMSEA	χ^2/sd
500	ML	X -> M: 0.6	0.616 (0.070)	***	0.016	0.991	0.989	0.029	1.415
500	ML	M -> Y: 0.7	0.539 (0.075)	***	-0.161				
500	ML	X -> Y: 0.3	0.265 (0.074)	***	-0.035				
500	ML	X-> M -> Y: 0.42	0.332 (0.054)	(0.232-0.448)	-0.088				

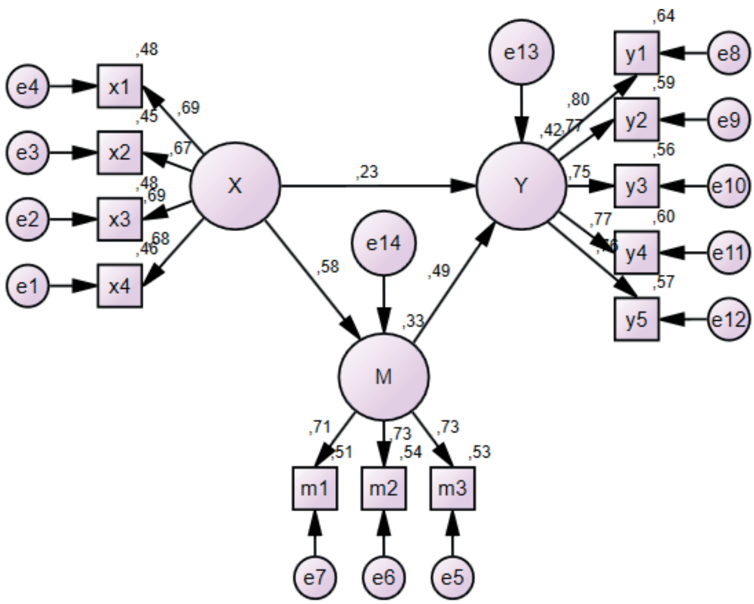


Figure 20. Amos path diagram N=500

In this volume, the closeness to the real values is a little better. This situation is accompanied by the model fit values. There is a similar result in the other first two programs. We can say that a single path coefficient is farther from the convergence point than the others. The path coefficient from M to Y was assigned as 0.7 as the real value and a good closeness to this value has not been achieved yet.

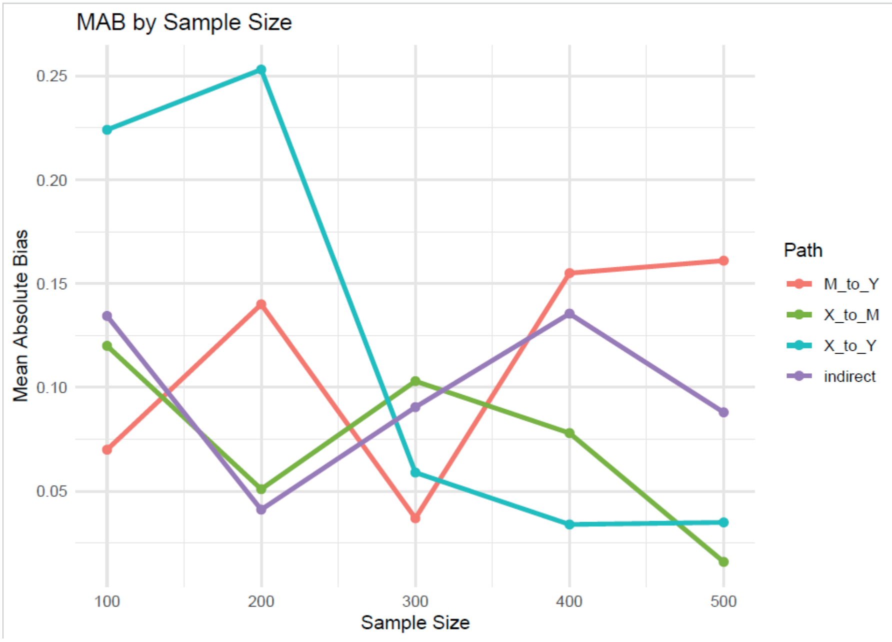


Figure 21. Amos MAB value

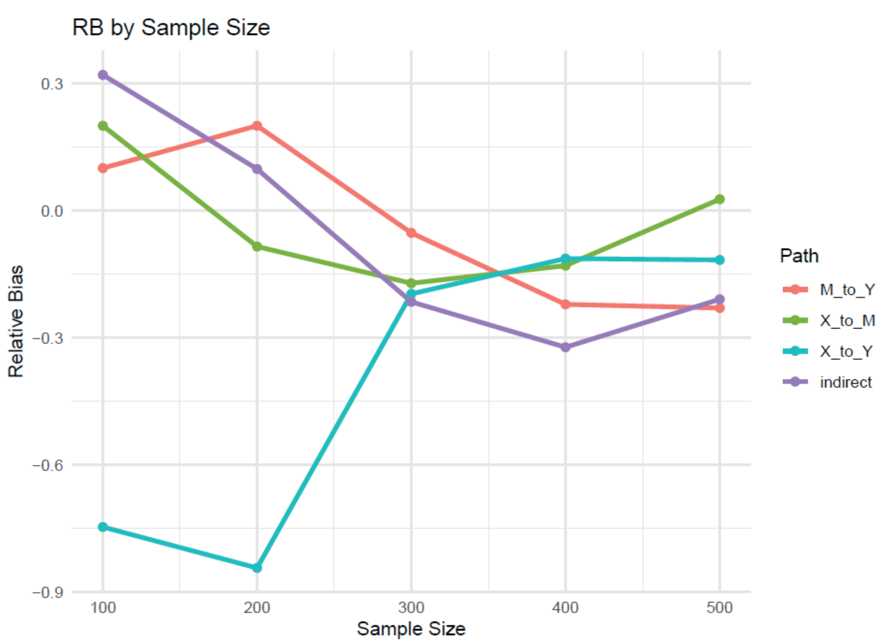


Figure 22. Amos RB value

We can say that the Amos program lags behind the other two programs in terms of bias with ML and Bootstrapping approaches. However, similarly, less bias was obtained in the Amos program at 300 units. However, when looking at the MAB values, a deviation of over 10% was recorded even at 300 units. This situation is over 15% at volumes of 400 and 500 units. Relative bias indicates that the excess seen in the MAB value is slightly less. When we consider all three programs, the least bias order is Mplus, Jamovi and Amos.

Outputs of Spss Program

Spss, Hayes' Process extension and OLS and Bootstrapping approaches were used to estimate the model. In this program, a selection process cannot be performed to determine the estimation techniques. However, unlike other programs, an input must be given according to the models enumerated by Hayes. The technique does not present a structure that can handle the measurement model while working with latent variables. Therefore, there is already a direct weakness. However, its frequent use by practitioners is present in many disciplines. Therefore, this program and technique that will reflect the purpose of the study were considered. Researchers working with latent variables need to specify each latent variable as a single variable when using this program. This eliminates the measurement model and calculates the average values of the latent variables and obtains a single variable. The outputs of the program are given below. Since path diagrams are given in other program outputs, they were also intended to be given here. For this, visuals were obtained through the R program.

Table 16. Spss sample size 100

Sample	**Estimator**	**Path Coefficient :True Value**	**Estimated Value (S.E)**	**p Value (LLCI-ULCI)**	**Difference**
100	OLS	X -> M: 0.6	0.5224 (0.1008)	0.000 (0.3222- 0.7225)	-0.0776
100	OLS	M -> Y: 0.7	0.5208 (0.0847)	0.000 (0.3526- 0.6889)	-0.1792
100	OLS	X -> Y: 0.3	0.1678 (0.0955)	0.082 (-0.0217- 0.3573)	-0.1322
100	OLS	X-> M -> Y: 0.42	0.2720 (0.0631)	(0.1604- 0.4077)	-0.1480
Model Fit	$\boldsymbol{R}$	$\boldsymbol{R}^2$	**Mean Squared Error- MSE**	$\boldsymbol{F(df_1, df_2)}$	**p Value**
	0.6329	0.4005	0.7728	32.4037(2,97)	0.000

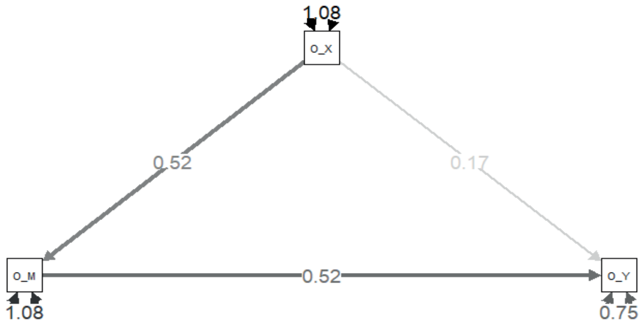


Figure 23. R path diagram N=100

Underestimation at 100 units and the direct effect of X on Y were obtained as insignificant in this program as in the other three programs. It is seen that the other path coefficients are significant. It is seen that the fit value is good. The 100-unit sample size also transformed the partial mediation model into a full mediation model in the Spss program. In addition, the explained variance for Y was obtained as 40.05%.

Table 17. Spss sample size 200

Sample	Estimator	Path Coefficient :True Value	Estimated Value (S.E)	p Value (LLCI-ULCI)	Difference
200	OLS	X -> M: 0.6	0.4081 (0.0658)	0.000 (0.2785- 0.5378)	-0.1919
200	OLS	M -> Y: 0.7	0.5200 (0.0629)	0.000 (0.3960- 0.6441)	-0.1800
200	OLS	X -> Y: 0.3	0.1436 (0.0636)	0.0251 (0.0181- 0.2690)	-0.1564
200	OLS	X-> M -> Y: 0.42	0.2122 (0.0415)	(0.1373- 0.2983)	-0.2078
Model Fit	***R***	***R*²**	**Mean Squared Error- MSE**	$F\left(df_1, df_2\right)$	**p Value**
	0.5910	0.3492	0.8473	52.8573(2,197)	0.000

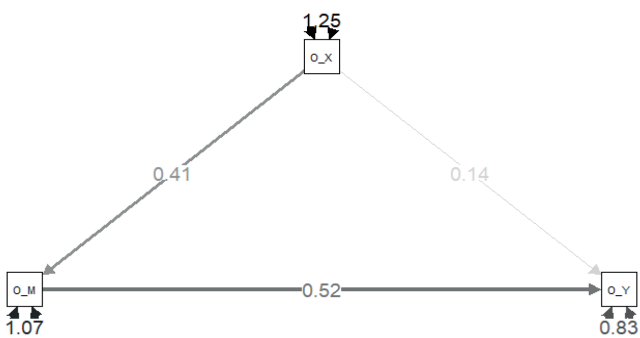


Figure 24. R path diagram N=200

In 200 units, underestimation and the direct effect of X on Y were obtained as insignificant. In this case, the model again turns into a full mediation model. In addition, the model fit value seems good. The explained variance rate for Y decreased to 34.92%.

Table 18. Spss sample size 300

Sample	Estimator	Path Coefficient :True Value	Estimated Value (S.E)	p Value (LLCI-ULCI)	Difference
300	OLS	X -> M: 0.6	0.3869 (0.0566)	0.000 (0.2755- 0.4982)	-0.2131
300	OLS	M -> Y: 0.7	0.4621 (0.0503)	0.000 (0.3631- 0.5610)	-0.2379
300	OLS	X -> Y: 0.3	0.2474 (0.0528)	0.000 (0.1434- 0.3514)	-0.0526
300	OLS	X-> M -> Y: 0.42	0.1788 (0.0305)	(0.1208- 0.2443)	-0.2412
Model Fit	R	R^2	**Mean Squared Error- MSE**	$F\left(df_1, df_2\right)$	**p Value**
	0.5913	0.3496	0.8677	79.8330(2,297)	0.000

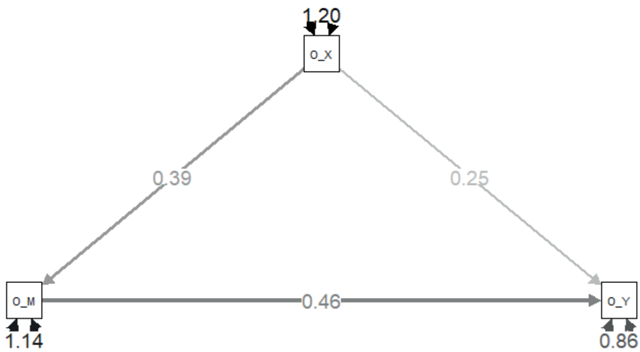


Figure 25. R path diagram N=300

It is seen that all path coefficients are significant in 300 units and underestimation occurs. The model fit value has been well-confirmed. The explained variance for Y is 34.96%, which is quite close to the previous sample size. Even though there are significant path coefficients in 300 units, it is obvious that they are quite far from the real values and also far from the estimated values obtained in 300 units in the other three programs.

Table 19. Spss sample size 400

Sample	Estimator	Path Coefficient :True Value	Estimated Value (S.E)	p Value (LLCI-ULCI)	Difference
400	OLS	X -> M: 0.6	0.3791 (0.0522)	0.000 (0.2764- 0.4817)	-0.2209
400	OLS	M -> Y: 0.7	0.4626 (0.0423)	0.000 (0.3794- 0.5458)	-0.2374
400	OLS	X -> Y: 0.3	0.2493 (0.0469)	0.000 (0.1571- 0.3416)	-0.0507
400	OLS	X-> M -> Y: 0.42	0.1754 (0.0281)	(0.1225- 0.2323)	-0.2446
Model Fit	***R***	R^2	**Mean Squared Error- MSE**	$F(df_1, df_2)$	**p Value**
	0.5901	0.3482	0.8860	106.0592(2,397)	0.000

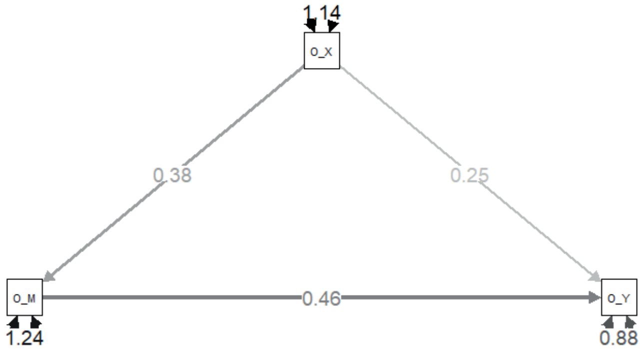


Figure 26. R path diagram N=400

The model fit is good at 400 units, the path coefficients are significant but far from the true values. Even in this state, 34.82% of the variance in Y is explained. When looking at other program outputs, it can be observed that the distance of the estimated values from the true values is not at this size.

Table 20. Spss sample size 500

Sample	Estimator	Path Coefficient :True Value	Estimated Value (S.E)	p Value (LLCI-ULCI)	Difference
500	OLS	X -> M: 0.6	0.4713 (0.0429)	0.000 (0.3889- 0.5573)	-0.1269
500	OLS	M -> Y: 0.7	0.4016 (0.0412)	0.000 (0.3206- 0.4826)	-0.2984
500	OLS	X -> Y: 0.3	0.2589 (0.0440)	0.000 (0.1725- 0.3454)	-0.0411
500	OLS	X-> M -> Y: 0.42	0.1900 (0.0254)	(0.1423- 0.2432)	-0.2300
Model Fit	***R***	R^2	**Mean Squared Error- MSE**	$F(df_1, df_2)$	**p Value**
	0.5579	0.3112	0.9350	112.2813(2,497)	0.000

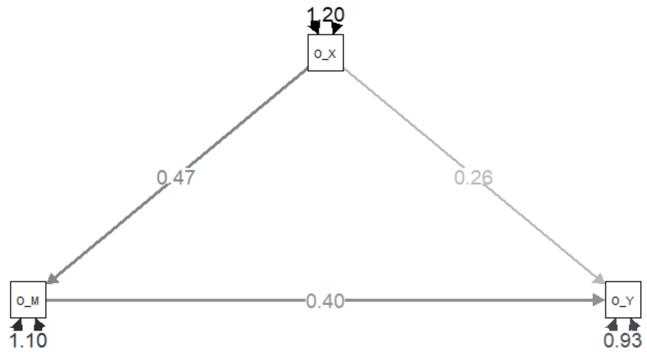


Figure 27. R path diagram N=500

The variance explained for Y in 500 units has a decrease of 31.12% and the model fit is good but the closeness to the real values is quite weak. When we look at the closeness to the real value in 500 units in other programs, we can say that Spss is quite behind at this point. In fact, this situation is present in the entire sample size.

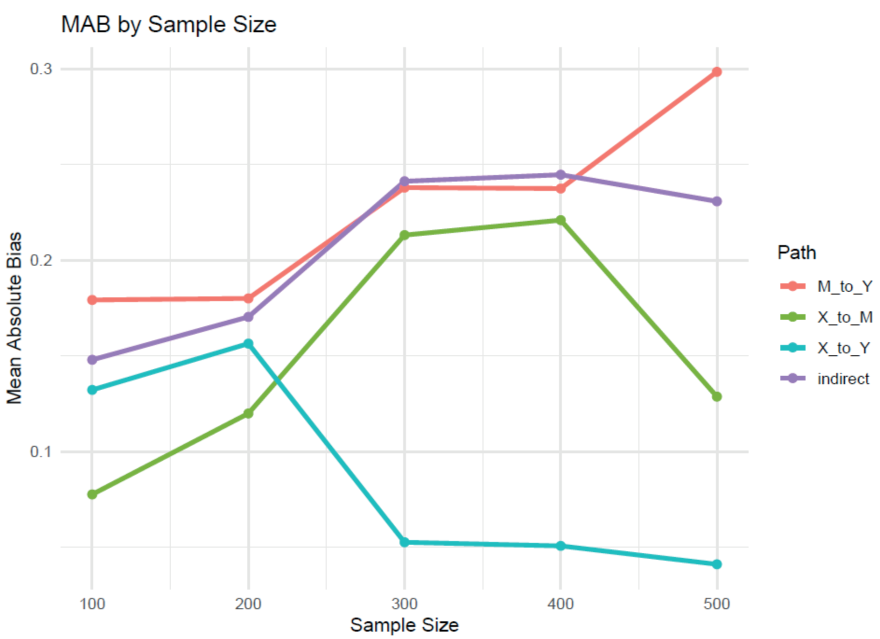


Figure 28. Spss MAB value

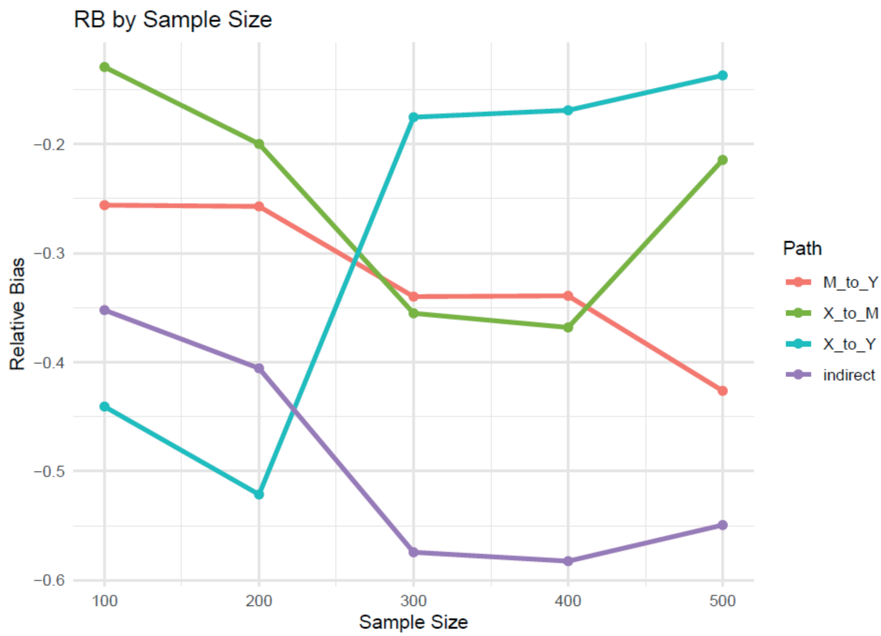


Figure 29. Spss RB value

In the simulation study conducted with the Hayes plugin of the Spss program, biases not seen in other programs were detected. While the other three programs gave the least bias in 300 units, they also showed low biases in the other 400 and 500 units. However, Spss produced estimation results that we can call quite weak together with OLS and Bootstrappig. This situation may be due to the model not addressing the measurement model. Relative biases have quite high deviations such as -60%. It is obvious that this result will lead to incorrect estimation of the model by being far from the threshold values given in the literature. The path coefficients did not follow a certain trend in any sample size and gave a rather scattered deviation image. The MAB values also indicate the same high deviations as the RB values, in other words, biases.

DISCUSSION AND CONCLUSION

This study aims to measure the performances of Mplus, Jamovi, Amos and Spss package programs, which are frequently used by applied researchers for the partial mediation model. The study aimed to attract the attention of applied researchers through the names of the package programs instead of an intensive process with theoretical information. The reason for this situation is that the examination of the performances of WLSMV, DWLS, ML and

OLS estimation techniques is likely to be seen as a more theoretical study by applied researchers. The simple partial mediation model (Çağlayan and Özenç, 2024; Hayes, 2018) was determined as a model frequently used by applied researchers. In assigning the real value for the model, it was thought that the model could transform into a different model in low sample sizes by assigning the X-->Y low path coefficient value, which is the most important of the direct effects. Previous studies (Forero and Maydeu-Olivares, 2009; Li, 2021; Yang-Wallentin et al., 2010) were used for the previously assigned values in the simulation. In addition, categorical data were obtained for the model in the data generation process. Only path coefficients were examined as a performance measure in the study. The study has many limitations as such. For example, standard errors, model fit values, missing data, and skewed data that do not provide normality were not addressed.

The sample size used in the study is not like those used in similar simulation studies (Li, 2021). The reason for this situation is the desire to obtain performance findings in sample sizes frequently used by applied researchers. The deviations between the previously assigned path coefficients and the findings of the estimation techniques, in other words, biases, were addressed with MAB and RB values. In interpreting these values, studies in the literature (Curran et al., 1996; Bandalos, 2002; Flora & Curran, 2004; Kaplan, 1989; Yang-Wallentin et al., 2010) were used as a basis.

The analysis findings based on the sample size based on path coefficients indicate the following: In all programs at 100 and 200 units, the model changes from a partial mediation model to a full mediation model. The issue that causes this situation is that the direct effect of X on Y is assigned as low. This situation can also be observed in studies conducted with real data, so this issue is very important. Practical researchers need to pay attention to this critical path coefficient. Otherwise, the hypotheses turn into a dimension that will change from beginning to end. This situation actually points to an incorrectly specified model study. Studies in the literature regarding an incorrectly specified model (Lai, 2018) should be examined.

The analysis findings have quite good results in all sample sizes. We see that the results such as incorrect specification of the model in 100 and 200 units are eliminated in the sample size of 300 units. In all programs, the first sample size in which all path coefficients are significant is determined as 300. Path coefficients are also significant in 400 and 500 units. In the evaluation of biases of the programs, RB values and MAB values were examined based on previous studies (Curran et al., 1996; Bandalos, 2002; Flora & Curran, 2004; Kaplan, 1989; Yang-Wallentin et al., 2010). When the analysis findings are examined, the biases in each sample size in the Hayes plugin of Spss are at a level that can be considered excessive. Therefore, we can say that this program, which does not take into account the measurement model, is quite weak in determining relationships supported by hypotheses and theories such as the mediation model. If a ranking is to be made between the other three programs, the outputs of the Mplus program showed the least bias. Thus, we can say that the WLSMV technique performs better than DWLS and ML.

The second place was taken by the Jamovi program when we look at it again within the framework of biases. With this result, we can say that the DWLS technique performs better than ML in categorical data. According to the available findings, the comments are not very clear when we consider the limitations of the study. However, despite the shortcomings of the study, a clear statement would be not to perform the mediation analysis in the Spss program. A clearer statement among other estimation techniques can only be achieved if issues such as missing data, standard errors, failure to provide multivariate normality, fit values and factor loadings are addressed in the simulation setup.

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Conflict of Interest

The study is a single author and has declared that there is no conflict of interest.

Author Contributions

The study is a single author and all contributions belong to the author.