How to interpret SEM model fit results in AMOS

There are several fit indices used in SEM, and the criteria for satisfactory fit can vary depending on the specific model being tested, the sample size, and the complexity of the model. However, there are some commonly used fit indices that are recommended to be considered when assessing model fit in SEM. These include:

- Chi-square divided by degrees of freedom (CMIN/DF*).
- Root mean square error of approximation (RMSEA*).
- Goodness of fit Index (GFI*).
- Comparative fit index (CFI*).
- Tucker-Lewis index (TLI *).

* Parameters/Values of particular interest

It's important to note that these fit indices are not independent of each other and should be considered together to assess model fit. Additionally, the choice of fit indices can vary depending on the research question and the specific model being tested.

❖ Where to find and how to interpret all SEM model fit parameters in AMOS.

How to present in research papers:

Acronym	Explication	Accepted fit	Resulting fit
CMIN/DF	Chi-square divided by degrees of freedom	≤ 3 it indicates an acceptable fit ≤ 5 it indicates a reasonable fit	
RMSEA	Root mean square error of approximation	≤ 0,05 are considered excellent ≤ 0,08 are considered acceptable	
GFI	Goodness of fit Index	≥ 0,90 indicates a reasonable fit ≥ 0,95 is considered an excellent fit	
CFI	Comparative fit index	≥ 0,90 indicates an acceptable fit ≥ 0,95 is considered an excellent fit	
TLI	Tucker-Lewis index	≥ 0,9 indicates a reasonable fit ≥ 0,95 is considered an excellent fit	
…			

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Adjustments to the SEM model in AMOS consist of adjusting the following parameters/indexes:

➢ Chi-square (CMIN)

The **CMIN** table can be found under: **View → Text Output → Model fit → CMIN**

CMIN

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	33	37,400	16	0,061	1,900
Saturated model	50	0	0		
Independence model	9	4800,00	49	0	120,000

❖ NPAR

NPAR = Number of parameters for each model (default, saturated and independent).

NPAR is the number of parameters in the model.

In the saturated (newly identified) model, there are 50 parameters.

There are 33 parameters for our tested (default) model.

For an independence model (one where all paths are deleted) there are 9 parameters (variances of 9 variables).

❖ CMIN or χ2 or Chi-square

CMIN or χ2 is the chi-square statistic that compares the tested model and the independence model to the saturated model.

The chi-square test tests the fit of the data by structural analysis of covariance assessing the fit of the samples and the covariance matrix (Barrett, 2007, Berry, 1994).

CMIN are 37,400 for our tested (default) model.

❖ DF

DF = degree of freedom measures the number of independent values that can be varied without disturbing the constraints in the model.

DF are 16 for our tested (default) model.

❖ P or $\chi^2_{significance}$

P or $\chi^2_{significance}$ or Likelihood Ratio is the statistical significance of the model.

Interpretation:	
A value p ≥ 0,05 indicates an acceptable fit	Joreskog & Surbom, 1996
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A value p = 0,061 it indicates an acceptable fit

❖ CMIN/DF or χ^2/df *

CMIN/DF or (χ^2/df) is the relative chi-square index, and it is how much the fit of the data to the model is reduced by dropping one or more paths.

Interpretation:	
If the CMIN/DF value is ≤ 2 it indicates an acceptable fit	Byrne, 1989, S.55
If the CMIN/DF value is ≤ 2 it indicates an acceptable fit	Tabachnick & Fidell, 2007
If the CMIN/DF value is ≤ 3 it indicates an acceptable fit	Kline, 1998
If the CMIN/DF value is ≤ 3 it indicates an acceptable fit	Homburg/Giering, 1966, S.13
If the CMIN/DF value is ≤ 5 it indicates a reasonable fit	Marsh & Hocevar, 1985
If the CMIN/DF value is ≤ 5 it indicates a reasonable fit	Wheaton et al, 1977, S.84 ff.
A CMIN/DF ratio of less than 2,0	Bentler and Bonett, 1980; Carmines and McIver, 1981; Kelloway, 1996
A CMIN/DF ratio of less than 3,0	Hu and Bentler, 1999
A CMIN/DF ratio of less than 5,0	Marsh et al., 2004
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CMIN/DF = 1,900 it indicates an acceptable fit

➢ Goodness of fit Index (GFI)

The **RMR, GFI** table can be found under: **View → Text Output → Model fit → RMR, GFI**

RMR, GFI

Model	RMR	GFI	AGFI	PGFI
Default model	0,148	0,965	0,944	0,623
Saturated model	0	1		
Independence model	0,152	0,876	0,567	0,345

❖ RMR

RMR = Root Mean Square Residual.

Reference values for RMR (Root Mean Square Residual) depend on the size of the model, the number of variables, and the values of other fit indices. There is no one specific set of reference values that can be universally applied, as different studies may have different expectations for what constitutes an acceptable level of RMR.

Interpretation:	
A value RMR = 0 represents a perfect fit.	
A value RMR <0,05 indicates an acceptable fit	
RMR ≤ 0.05 = acceptable fit	Diamantopoulos & Siguaw , 2000
RMR ≤ 0.07 = acceptable fit	Steiger, 2007
Some commonly used thresholds for RMR include values less than 0,08 or less than 0,05	Hu & Bentler, 1999; Kline, 2016
The smaller the RMR value the better.	
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It is important to note that these thresholds are not absolute and should be considered in conjunction with other fit indices when evaluating model fit.

RMR are 0,148 for our tested (default) model.

❖ GFI *

GFI stands for Goodness of fit Index and is used to calculate the minimum discrepancy function necessary to achieve a perfect fit under maximum likelihood conditions (Jöreskog & Sörbom, 1984; Tanaka & Huba, 1985). The Goodness of fit Index (GFI) is a measure of how well the model fits the data, with values ranging from 0 to 1.

GFI = Goodness of fit Index and takes values of ≤ 1.

Interpretation:	
A value GFI = 1 represents a perfect fit.	
Higher values indicate a better fit.	
A value GFI ≥ 0,9 indicates a reasonable fit	Hu & Bentler, 1998
values above 0,90 indicate a good fit	Hair, Anderson, Tatham, and Black, 1998
A value GFI ≥ 0,9 indicates a reasonable fit	Homburg/Baumgartner, 1988, S.363
A value GFI ≥ 0,95 is considered an excellent fit	Kline, 2005
suggests that values between 0,90 and 0,95 are acceptable fit and values above 0,95 are excellent fit	Kline, 2016
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GFI are 0,965 for our tested (default) model, this is considered an excellent fit.

❖ AGFI

AGFI = Adjusted Goodness of fit Index and indicates the degree of freedom (df) for testing the model. A value of 1 indicates a perfect fit. Unlike GFI, AGFI values do not stop at 0.

The reference values for AGFI (Adjusted Goodness of fit Index) may vary depending on the specific research field and the complexity of the model. It is important to note that these are general guidelines and the specific threshold for an acceptable fit may vary depending on the research context and the complexity of the model.

Interpretation:	
A value AGFI = 1 represents a perfect fit.	
A value AGFI ≥ 0,9 indicates a reasonable fit	Bagozzi/Yi, 1988, S.82
A value AGFI ≥ 0,9 indicates a acceptable fit	Tabachnick & Fidell, 2007
AGFI values greater than 0,90 indicate an acceptable fit, while values greater than 0,95 indicate a good fit	Hair et al., 2017
AGFI value of 0,80 or greater indicates an acceptable fit.	Hu and Bentler, 1999
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AGFI are 0,944 for our tested (default) model, this is considered an excellent fit.

❖ PGFI

PGFI = Parsimony Goodness of fit Index is a modification of GFI (Mulaik et al.,1989) and calculates the degree of freedom for the model.

PGFI (Adjusted Goodness of fit Index) is not a commonly used fit index in structural equation modeling, so there are no established reference values for it. PGFI is a modification of the GFI that adjusts for the complexity of the model and the number of estimated parameters.

The reference values may depend on the complexity of the model and the sample size.

Interpretation:	
A value PGFI = 1 represents a perfect fit.	
A value PGFI > 0,50 indicates an acceptable fit	
PGFI value of 0,5 or greater indicates an acceptable fit	Joreskog & Sorbom, 1993
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PGFI are 0,623 for our tested (default) model, indicates an acceptable fit.

➢ Baseline Comparisons

The **Baseline Comparisons** table can be found under: **View → Text Output → Model fit → Baseline Comparisons**

Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	0,989	0,965	0,987	0,965	0,987
Saturated model	1		1		1
Independence model	0	0	0	0	0

❖ NFI

NFI = Normed fit Index also called Delta 1 (Bollen, 1898b), which consists of scaling values between the (terribly fitting) independence model and the (perfectly fitting) saturated model.

Interpretation:	
A value of NFI = 1 indicates a perfect fit.	
While models with a value NFI < 0,9 can usually be significantly improved	Bentler & Bonett, 1980
A value NFI ≥ 0,9 indicates a reasonable fit	Bentler & Bonett, 1980
Suggested that values above 0.95 indicate a good fit, values between 0.90 and 0.95 indicate an acceptable fit, and values below 0.90 indicate a poor fit.	Hu and Bentler 1999
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NFI are 0,989 for our tested (default) model, this is considered an excellent fit.

❖ RFI

RFI = Relative fit Index and derived from NFI. The reference values for RFI (Relative fit Index) are not as established as for other fit indices.

The reference values may depend on the complexity of the model and the sample size.

Interpretation:	
A value of RFI = 1 indicates a perfect fit.	
A value of RFI closed to 1 indicate a very good fit	
A value RFI ≥ 0,9 indicates a reasonable fit	
suggest that values above 0.90 indicate an acceptable fit, and values above 0.95 indicate a good fit	Hu and Bentler, 1999
recommends a cutoff of 0.90 for acceptable fit, but notes that the reference values may depend on the complexity of the model and the sample size.	Kline, 2011
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RFI are 0,965 for our tested (default) model, this is considered an excellent fit.

❖ IFI

IFI = Incremental fit Index.

Interpretation:	
A value of IFI = 1 indicates a perfect fit.	
A value of IFI closed to 1 indicate a very good fit	
A value IFI ≥ 0,9 indicates a reasonable fit	
Suggest that IFI values of 0,90 or higher indicate good model fit, while values between 0,80 and 0,90 suggest acceptable fit	Bentler, 1990; Hu & Bentler, 1999
Suggested more conservative cutoffs, such as IFI values of 0,95 or higher for good fit	Marsh, Hau, & Wen, 2004
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It's important to note that reference values for IFI can vary depending on the complexity and size of the model, as well as the sample size and characteristics of the population being studied. Therefore, researchers should interpret IFI values in the context of their specific analysis and use their judgment to determine what constitutes acceptable or good fit.

IFI are 0,987 for our tested (default) model, this is considered an excellent fit.

❖ TLI *

TLI = Tucker-Lewis coefficient also known as Bentler-Bonett non-normed fit index (NNFI) ranges from (but not limited to) 0 to 1 where a value closer to 1 represents a very good fit while 1 represents a perfect fit.

The reference values for TLI (Tucker-Lewis Index) vary depending on the sample size and complexity of the model.

Interpretation:	
A value of TLI = 1 indicates a perfect fit.	
Some researchers have suggested that TLI values above 0,80 are acceptable in smaller samples or less complex models.	
For the model to be acceptable it should have a TLI value higher than 0,9	Brown, 2006
For an excellent model it is necessary that the TLI value be higher than 0,95	Brown, 2006
A value TLI ≥ 0,9 indicates a reasonable fit	
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TLI are 0,965 for our tested (default) model, this is considered an excellent fit.

❖ CFI *

CFI = Comparative fit Index has value truncated between 0 and 1.

Interpretation:	
A value of CFI = 1 indicates a perfect fit.	Hu & Bentler, 1999
A values of CFI closed to 1 show a very good fit.	
A CFI value of ≥ 0,95	Hu & Bentler, 1999
A CFI value of ≥ 0,90	Homburg/Baumgartner, 1998, S.363
A value CFI ≥ 0,90 indicates an acceptable fit	Fan et al., 1999
A CFI value of ≥ 0,95 is considered an excellent fit for the model	West et al., 2012
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CFI are 0,987 for our tested (default) model, this is considered an excellent fit.

➢ Parsimony-Adjusted Measures

The **Parsimony-Adjusted Measures** table can be found under: **View → Text Output → Model fit → Parsimony-Adjusted Measures**

Parsimony-Adjusted Measures

Model	PRATIO	PNFI	PCFI
Default model	2,398	0,694	0,694
Saturated model	0	0	0
Independence model	1	0	0

❖ PRATIO

PRATIO is the ratio of how many tracks/paths you fell to how many you could have fallen (all of them).

PRATIO = parsimony ratio that calculates the number of constraints in the model and is used to calculate the PNFI and PCFI indices.

PRATIO, or the ratio of the chi-square values of the target model to the null model, is a goodness-of-fit index commonly used in structural equation modeling. It measures the improvement in model fit when adding a path or a set of paths to the null model. The reference values for PRATIO depend on the degrees of freedom of the target model, the number of parameters estimated, and the level of significance.

Interpretation:	
PRATIO value greater than 1 suggests that the target model fits the data better than the null model, while a PRATIO value close to 1 indicates poor model fit	
Suggest that a PRATIO value of 2 or greater indicates good model fit	Bollen, 1989; Hu & Bentler, 1999
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There is no universally accepted cutoff value for PRATIO, as it depends on the specific model and sample size.

PRATIO = 2,398 indicates good model fit.

❖ PNFI

PNFI The Parsimion Normalized fit Index is a product of NFI and PRATIO.

PNFI = Normalized fixed parsimony index, which expresses the result of parsimony adjustment (James, Mulaik & Brett, 1982) according to the normalized fixed index (NFI).

PNFI (Parsimony Normed fit Index) and PCFI are fit indices in SEM that take into account the complexity of the model.

There is no universally accepted standard or reference value for PNFI and PCFI.

Interpretation:	
PNFI value of 0.5 or higher indicate acceptable model fit	Hu & Bentler, 1999
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PNFI = 0,694 indicates good model fit.

❖ PCFI

PCFI = Comparative Fixed Parsimony Index which expresses the result of the parsimony adjustment applied to the Comparative fit Index (CFI). PCFI is a product of CFI and PRATIO

PNFI and PCFI (Parsimony Comparative fit Index) are fit indices in SEM that take into account the complexity of the model.

There is no universally accepted standard or reference value for PNFI and PCFI.

Interpretation:	
PCFI value of 0.6 or higher indicate acceptable model fit	Hu & Bentler, 1999
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PCFI = 0,694 indicates good model fit.

➢ NCP

The **NCP** table can be found under: **View → Text Output → Model fit → NCP**

NCP

Model	NCP	LO 90	HI 90
Default model	1,900	1,500	2,300
Saturated model	0	0	0
Independence model	3456,789	3344,222	4433,123

❖ NCP

NCP = value of non-centrality parameter with bounds expressed as LO (NcpLo) and Hi (NcpHi), respectively the lower and upper bounds of the 90% confidence interval for NCP.

The Normalized Chi-Square (NCP) is a fit index that measures the discrepancy between the observed covariance matrix and the implied covariance matrix derived from the model. It is calculated by dividing the chi-square value by its degrees of freedom and then by the number of observations. The reference values for NCP depend on the specific model and the number of variables and indicators included.

Interpretation:	
General guidelines suggest that: NCP values less than 2 indicate an acceptable fit, while NCP values between 2 and 3 indicate a marginally acceptable fit, and NCP values greater than 3 indicate a poor fit	Kline, 2011
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LO 90 = 1,500 Lower limit (NCPLo method) of the 90% confidence interval for NCP.

HI 90 = 2,300 Upper bound (NCPHi method) 90% confidence interval for NCP.

From the example table above, the population NCP = 1,900 for the default model is between 1,500 and 2,300 with a confidence level of approximately 90 percent. NCP = 1,900 , values less than 2 indicate an acceptable fit.

➢ FMIN

The **FMIN** table can be found under: **View → Text Output → Model fit → FMIN**

FMIN

Model	FMIN	F0	LO 90	HI 90
Default model	0,046	0,044	0,022	0,044
Saturated model	0	0	0	0
Independence model	4,567	4,577	5,234	5,244

❖ FMIN

FMIN = Model fit index with bounds expressed as LO and HI, or lower and upper bounds of the 90% confidence interval for FMIN. A value closer to 0 represents a better fit of the model to the observed data, with 0 being a perfect fit.

F0 = Confidence interval

FMIN (Function Minimum Fit Function) is a measure of model fit in structural equation modeling (SEM) that represents the difference between the observed and predicted covariance matrix. The lower the value of FMIN, the better the fit of the model. However, there are no established reference values for FMIN, as the value of FMIN depends on the complexity of the model and the size of the sample.

Therefore, there are no specific reference values for FMIN, and it is generally used as a comparative measure to evaluate the fit of different models or modifications to a given model.

Interpretation:	
A value closer to 0 represents a better fit of the model to the observed data, with 0 being a perfect fit.	
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LO 90 = 0,022 Lower boundary of the 90% confidence interval of FMIN.

HI 90 = 0,044 Upper boundary of the 90% confidence interval of FMIN.

From the table above, we see that the Fit Index of the FMIN model for the given model is between 0,022 and 0,044 with a confidence level of approximately 90 percent, which represents an excellent fit of the model.

➢ RMSEA

The **RMSEA** table can be found under: **View → Text Output → Model fit → RMSEA**

RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	0,030	0,015	0,055	0,654
Independence model	0,345	0,356	0,367	0

❖ RMSEA *

RMSEA = Root Mean Square Error of Approximation is a goodness-of-fit index in SEM that assesses the discrepancy between the observed covariance matrix and the model-implied covariance matrix, taking into account model complexity.

Interpretation:	
The smaller the RMSEA value, the better the model fit.	
RMSEA values higher than 0,1 are considered poor, RMSEA values between 0,08 and 0,1 are considered borderline, values ranging from 0,05 to 0,08 are considered acceptable, and RMSEA values ≤ 0,05 are considered excellent	MacCallum et al, 1996
an RMSEA value below 0,05 indicates good fit, a RMSEA value between 0,05 and 0,08 indicates acceptable fit, and a RMSEA value above 0,10 indicates poor fit	Browne & Cudeck, 1993; Hu & Bentler, 1999; Kline, 2016
0,05 ≤ RMSEA ≤ 0,08 are considered acceptable,	Browne, Cudeck, 1993, S.144
RMSEA < 0,1 are considered acceptable, RMSEA < 0,06 are considered excellent	Hu and Bentler, 1999
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LO 90 = 0,015 Lower boundary (RmseaLo) of a 90% confidence interval of the RMSEA.

HI 90 = 0,055 Higher boundary (RmseaHi) of a 90% confidence interval of the RMSEA.

❖ PCLOSE

PCLOSE is a test of close fit for the model in structural equation modeling (SEM). It is typically used in conjunction with other fit indices, such as the root mean square error of approximation (RMSEA) and comparative fit index (CFI), to evaluate model fit.

There is no single agreed-upon reference value for PCLOSE. However, some researchers have suggested using a cutoff value of 0,05, meaning that if PCLOSE is greater than 0,05, the model is considered to have close fit. Others have suggested using a more stringent cutoff of 0,01 or 0,001.

It is worth noting that the appropriateness of using PCLOSE as a test of close fit has been called into question by some researchers, as it is sensitive to sample size and model complexity. Instead, some researchers recommend using multiple fit indices, along with other model evaluation techniques such as modification indices and residual plots, to thoroughly evaluate model fit.

PCLOSE = 0,654 P-value of the null hypothesis

The obtained RMSEA values for this model is RMSEA = 0,030 and show that this model is adequate. From the table above, we see that the root mean square error of approximation RMSEA for the given model is between 0,015 and 0,055 with a confidence level of approximately 90 percent, which represents an excellent fit of the model. PCLOSE = 0,654 so it is greater than 0.05 and the model is considered to have close fit.

➢ AIC

The **AIC** table can be found under: **View → Text Output → Model fit → AIC**

AIC

Model	AIC	BCC	BIC	CAIC
Default model	123,567	131,132	267,890	344,555
Saturated model	121	123,456	345,876	456,876
Independence model	4321,123	4321,789	5432,89	5432,90

❖ AIC

AIC stands for Akaike Information Criterion (Akaike, 1987) and is used to measure the quality of the statistical model for the data sample used. AIC score useful only in comparison with other AIC scores of the same data set.

The lower the AIC value, the better.

AIC = 123,567

❖ BCC

BCC = Browne-Cudeck criterion used specifically to analyze moment structures and impose a larger penalty on less parsimonious models.

❖ BIS

BIC = Bayesian Information Criterion applies a larger penalty for complex models compared to AIC, BCC, CAIC and therefore has a greater tendency to select parsimonious models.

BIC = 267,890 for our tested (default) model.

❖ CAIC

CAIC = Consistent Akaike Information Criterion (Atilgan & Bozdogan, 1987) occurs only when means and intercepts are not explicit in the case of one group. CAIC applies a penalty to complex models that is higher than AIC and BCC, but less severe than BIC.

The reference values for these criteria depend on the sample size, number of parameters, and model complexity. As such, there are no fixed reference values. However, some guidelines suggest that models with lower AIC, BIC, BCC, and CAIC values are preferred over models with higher values.

Lower values of these criteria indicate better model fit.

➢ ECVI

The **ECVI** table can be found under: **View → Text Output → Model fit → ECVI**

ECVI

Model	ECVI	LO 90	HI 90	MECVI
Default model	0,123	0,145	0,167	0,189
Saturated model	0,11	0,12	0,13	0,134
Independence model	6,543	6,432	6,987	6,999

❖ ECVI

The Expected Cross-Validation Index (ECVI) is a measure of model fit used in SEM that estimates the expected prediction error of the model.

The formula for ECVI depends on the number of parameters in the model, the sample size, and the estimated model parameters. The smaller the ECVI value, the better the model fit. However, there are no universally accepted reference values for ECVI, as it is often used in conjunction with other fit indices to assess model fit.

ECVI = 0,123 for our tested (default) model.

LO 90 = lower limit of the 90% confidence interval for the ECVI population.

HI 90 = upper bound of the 90% confidence interval for the ECVI population.

MECVI = except for the scale factor used in the calculation, MECVI is similar to the Browne-Cudeck criterion (BCC).

➢ HOELTER Index

The **HOELTER** table can be found under: **View → Text Output → Model fit → HOELTER**

HOELTER

Model	HOELTER .05	HOELTER .01
Default model	435	422
Independence model	11	12

❖ HOELTER

Hoelter's critical N is a method used to determine the minimum sample size needed for a given level of statistical power in SEM. The critical N value indicates the minimum sample size at which the model's chi-square statistic reaches statistical significance at the desired level of power.

The reference values for Hoelter's critical N depend on the number of variables in the model and the desired level of statistical power.

Interpretation:	
HOELTER 0,05 ≥ 200 HOELTER 0,01 ≥ 200	Hoelter, 1983, s.325
Suggests that a critical N value of 200 or greater is considered adequate CN ≥ 200	Kelloway, 1998
Suggest that a critical N value of 100 or greater is acceptable CN ≥ 100	Hu and Bentler, 1999
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There is no universal set of reference values for Hoelter's critical N, as they vary depending on the specifics of the model being tested.

A values HOELTER 0,05 = 435 and HOELTER 0,01 = 422 are satisfactory sample sizes.

➢ SRMR

Standardized root mean square residual (SRMR)

❖ SRMR

The SRMR measures the average absolute difference between the observed and predicted correlations in the model.

Interpretation:	
SRMR ≤ 0.05 = acceptable fit	Diamantopoulos & Siguaw, 2000
A value below 0.08 is generally considered acceptable.	
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