

## Structural Equation Modeling

Structural equation modeling is a multivariate statistical analysis technique that is used to analyze structural relationships. This technique is the combination of [factor analysis](#) and [multiple regression analysis](#), and it is used to analyze the structural relationship between measured variables and latent constructs. This method is preferred by the researcher because it estimates the multiple and interrelated dependence in a single analysis. In this analysis, two types of variables are used endogenous variables and exogenous variables. Endogenous variables are equivalent to dependent variables and are equal to the independent variable.

### Theory:

This can be thought of as a set of relationships providing consistency and comprehensive explanations of the actual phenomena. There are two types of models:

1. **Measurement model:** The measurement model represents the theory that specifies how measured variables come together to represent the theory.
2. **Structural model:** Represents the theory that shows how constructs are related to other constructs.

Structural equation modeling is also called casual modeling because it tests the proposed casual relationships. The following assumptions are assumed:

1. **Multivariate normal distribution:** The maximum likelihood method is used and assumed for multivariate normal distribution. Small changes in multivariate normality can lead to a large difference in the chi-square test.
2. **Linearity:** A linear relationship is assumed between endogenous and exogenous variables.
3. **Outlier:** Data should be free of outliers. Outliers affect the model significance.
4. **Sequence:** There should be a cause and effect relationship between endogenous and exogenous variables, and a cause has to occur before the event.
5. **Non-spurious relationship:** Observed covariance must be true.
6. **Model identification:** Equations must be greater than the estimated parameters or models should be over identified or exact identified. Under identified models are not considered.
7. **Sample size:** Most of the researchers prefer a 200 to 400 sample size with 10 to 15 indicators. As a rule of thumb, that is 10 to 20 times as many cases as variables.
8. **Uncorrelated error terms:** Error terms are assumed uncorrelated with other variable error terms.
9. **Data:** Interval data is used.

### Steps:

1. **Defining individual constructs:** The first step is to define the constructs theoretically.

Conduct a pretest to evaluate the item. A confirmatory test of the measurement model is conducted using [CFA](#).

2. **Developing the overall measurement model:** The measurement model is also known as path analysis. [Path analysis](#) is a set of relationships between exogenous and endogenous variables. This is shown by the use of an arrow. The measurement model follows the assumption of unidimensionality. Measurement theory is based on the idea that latent constructs cause the measured variable and that the error term is uncorrelated within measured variables. In a measurement model, an arrow is drawn from the measured variable to the constructs.
3. **Design the study to produce the empirical results:** In this step, the researcher must specify the model. The researcher should design the study to minimize the likelihood of an identification problem. Order condition and rank condition methods are used to minimize the identification problem.
4. **Assessing the measurement model validity:** Assessing the measurement model is also called CFA. In CFA, a researcher compares the theoretical measurement against the reality model. The result of the CFA must be associated with the constructs' validity.
5. **Specifying the structural model:** In this step, structural paths are drawn between constructs. In the structural model, no arrow can enter an exogenous construct. A single-headed arrow is used to represent a hypothesized structural relationship between one construct and another. This shows the cause and effect relationship. Each hypothesized relationship uses one degree of freedom. The model can be recursive or non-recursive.
6. **Examine the structural model validity:** In the last step, a researcher examines the structural model validity. A model is considered a good fit if the value of the chi-square test is insignificant, and at least one incremental fit index (like CFI, GFI, TLI, AGFI, etc.) and one badness of fit index (like RMR, RMSEA, SRMR, etc.) meet the predetermined criteria.

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### Resources

Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modeling in practice: A review and recommended two-step approach. *Psychological Bulletin*, 103(3), 411-423.

Bentler, P. M., & Chou, C. -P. (1987). Practical issues in structural modeling. *Sociological Methods & Research*, 16(1), 78-117.

Bollen, K. A. (1989). *Structural equations with latent variables*. New York: John Wiley & Sons. [View](#)

Bollen, K. A. (1990). Overall fit in covariance structure models: Two types of sample size effects. *Psychological Bulletin*, 107(2), 256-259.

Bollen, K., & Lennox, R. (1991). Conventional wisdom on measurement: A structural equation perspective. *Psychological Bulletin*, 110(2), 305-314.

Boomsma, A. (2000). Teacher's corner: Reporting analyses of covariance structures. *Structural Equation Modeling: A Multidisciplinary Journal*, 7(3), 461-483.

Byrne, B. M. (1998). *Structural equation modeling with LISREL, PRELIS, and SIMPLIS: Basic concepts, applications, and programming*. Mahwah, NJ: Lawrence Erlbaum Associates. [View](#)

Byrne, B. M. (2001). *Structural equation modeling with AMOS: Basic concepts, applications, and programming*. Mahwah, NJ: Lawrence Erlbaum Associates.

Byrne, B. M. (2004). Testing for multigroup invariance using AMOS Graphics: A road less traveled. *Structural Equation Modeling*, 11(2), 272-300.

Chen, F., Bollen, K. A., Paxton, P., Curran, P. J., & Kirby, J. B. (2001). Improper solutions in structural equation models: Causes, consequences, and strategies. *Sociological Methods and*

*Research*, 29(4), 468-508.

Cheung, G. W., & Rensvold, R. B. (2002). Evaluating goodness-of-fit indexes for testing measurement invariance. *Structural Equation Modeling*, 9(2), 233-255.

Curran, P. J., Bollen, K. A., Paxton, P., Kirby, J., & Chen, F. (2002). The noncentral chi-square distribution in misspecified structural equation models: Finite sample results from a Monte Carlo simulation. *Multivariate Behavioral Research*, 37(1), 1-36.

Fan, X., Thompson, B., & Wang, L. (1999). Effects of sample size, estimation method, and model specification on structural equation modeling fit indexes. *Structural Equation Modeling*, 6(1), 56-83.

Hatcher, L. (1994). *A step-by-step approach to using the SAS system for factor analysis and structural equation modeling*. Cary, NC: SAS Institute.

Hipp, J. R., & Bollen, K. A. (2003). Model fit in structural equation models with censored, ordinal, and dichotomous variables: Testing vanishing tetrads. *Sociological Methodology*, 33, 267-305.

Hoyle, R. H. (Ed.). (1995). *Structural equation modeling: Concepts, issues, and applications*. Thousand Oaks, CA: Sage Publications.

Jöreskog, K. G. (1970). *A general method for estimating a linear structural equation system* (Report No. RB-70-54). Princeton, NJ: Educational Testing Service.

Jöreskog, K. G., & Yang, F. (1996). Non-linear structural equation models: The Kenny-Judd model with interaction effects. In G. A. Marcoulides & R. E. Schumacker (Eds.), *Advanced structural equation modeling* (pp. 57-88), Mahwah, NJ: Lawrence Erlbaum Associates.

Kline, R. B. (2005). *Principles and practice of structural equation modeling* (2nd ed.). New York: Guilford Press. [View](#)

Lee, S., & Hershberger, S. (1990). A simple rule for generating equivalent models in covariance structure modeling. *Multivariate Behavioral Research*, 25(3), 313-334.

Lee, S. (2007). *Structural equation modeling: A Bayesian approach*. New York: John Wiley & Sons.  
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Maruyama, G. M. (1998). *Basics of structural equation modeling*. Thousand Oaks, CA: Sage Publications. [View](#)

McDonald, R. P., & Ho, M. -H. R. (2002). Principles and practice in reporting structural equation analyses. *Psychological Methods*, 7(1), 64-82.

Mueller, R. O. (1996). *Basic Principles of structural equation modeling: An introduction to LISREL and EQS*. New York: Springer-Verlag. [View](#)

Mulaik, S. A., & Millsap, R. E. (2000). Doing the four-step right. *Structural Equation Modeling*, 7(1), 36-73.

Olsson, U. H., Foss, T., Troye, S. V., & Howell, R. D. (2000). The performance of ML, GLS, and WLS estimation in structural equation modeling under conditions of misspecification and nonnormality. *Structural Equation Modeling*, 7(4), 557-595.

Raykov, T. (2000). On the large-sample bias, variance, and mean squared error of the conventional noncentrality parameter estimator of covariance structure models. *Structural Equation Modeling*, 7(3), 431-441.

Raykov, T. (2005). Bias-corrected estimation of noncentrality parameters of covariance structure models. *Structural Equation Modeling*, 12(1), 120-129.

Raykov, T., & Marcoulides, G. A. (2006). *A first course in structural equation modeling* (2nd ed.). New York: Lawrence Erlbaum Associates. [View](#)

Raykov, T., Tomer, A., & Nesselroade, J. R. (1991). Reporting structural equation modeling results in Psychology and Aging: Some proposed guidelines. *Psychology and Aging*, 6(4), 499-503.

Schreiber, J. B. (2008). Core reporting practices in structural equation modeling. *Research in Social & Administrative Pharmacy*, 4(2), 83-97.

Schumacker, R. E. (2002). Latent variable interaction modeling. *Structural Equation Modeling*, 9(1), 40-54.

Schumacker, R. E., & Lomax, R. G. (2004). *A beginner's guide to structural equation modeling* (2nd ed.). London: Routledge. [View](#)

Shipley, B. (2000). *Cause and correlation in Biology: A user's guide to path analysis, structural equations and causal inference*. Cambridge, UK: Cambridge University Press. [View](#)

Sirtes, P., Richardson, T., Meek, C., Scheines, R., & Glymour, C. (1998). Using path diagrams as a structural equation modeling tool. *Sociological Methods & Research*, 27(2), 182-225.

Suyapa, E., Silva, M., & MacCallum, R. C. (1988). Some factors affecting the success of specification searches in covariance structure modeling. *Multivariate Behavioral Research*, 23(3), 297-326.

Thompson, B. (2000). Ten commandments of structural equation modeling. In L. Grimm & P. Yarnell (Eds.), *Reading and understanding more multivariate statistics* (pp. 261-284). Washington, DC: American Psychological Association.

Ullman, J. B. (2001). Structural equation modeling. In B. G. Tabachnick & L. S. Fidell (Eds.), *Using Multivariate Statistics* (4th ed.) (pp. 653-771). Needham Heights, MA: Allyn & Bacon.

Vermunt, J. K., & Magidson, J. (2005). Structural equation models: Mixture models. In *Encyclopedia of statistics in behavioral science* (pp. 1922-1927). Chichester, UK: John Wiley & Sons.

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