

CONFIRMATORY FACTOR ANALYSIS

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1. Core Definition and Purpose

Confirmatory Factor Analysis (CFA) is a powerful multivariate statistical technique used primarily within the framework of Structural Equation Modeling (SEM). Its fundamental purpose is to test, confirm, or refine hypothesized relationships between observed variables (indicators) and unobserved variables (latent factors or constructs). Unlike its predecessor, Exploratory Factor Analysis (EFA), CFA requires the researcher to specify the factor structure *a priori*, based on existing theory, previous research, or established scales. This anticipated structure involves defining precisely which observed variables load onto which latent factors, and whether these factors are correlated. CFA is one of a group of processes employed in factor analysis to show that a set of variables retains an **abstract anticipated factor construction**.

The mathematical model underpinning CFA attempts to account for the covariances or correlations among the observed variables by assuming they are generated by a smaller number of underlying latent variables. By subjecting the data to the hypothesized model, CFA assesses how well the theoretical factor structure actually fits the observed data structure. The outcome provides a rigorous statistical test of the measurement model, addressing crucial psychometric questions regarding the construct validity and reliability of measurement instruments. This analytical rigor is paramount in fields requiring precise measurement, such as developing personality inventories, assessing cognitive abilities, or measuring complex sociological constructs.

In practice, the success of a CFA model is determined by various fit indices that compare the covariance matrix implied by the researcher's theoretical model against the actual sample covariance matrix. A good fit indicates that the specified theoretical structure is statistically plausible given the observed data. This methodology is central to advancing measurement theory, ensuring that when researchers claim to be measuring a construct--such as depression, intelligence, or job satisfaction--their instruments are indeed measuring that intended abstract factor construction reliably and validly.

2. CFA Versus Exploratory Factor Analysis (EFA)

The distinction between CFA and Exploratory Factor Analysis (EFA) is crucial and defines the utility of each approach. EFA is typically used during the early stages of instrument development when the researcher has little or no theoretical expectation about the number of underlying factors or how the items relate to those factors. EFA is data-driven; it systematically identifies the underlying structure by grouping variables that exhibit high correlations, thereby exploring potential

latent dimensions. It allows all observed variables to load onto all factors, although the resulting loadings are usually rotated to achieve a simpler structure.

CFA, conversely, is hypothesis-driven and strictly confirmatory. It operates on the principle of constraint. In a CFA model, the researcher imposes specific constraints: they must explicitly set certain factor loadings to zero (i.e., specifying that a certain observed item does **not** measure a specific latent factor) and determine which factors are permitted to covary. This imposition of constraints means that CFA is a much more stringent test of theory than EFA. Because of this focus on testing established hypotheses rather than generating new ones, the source content correctly notes that confirmatory factor analysis is used more often than its exploratory counterpart, especially when dealing with well-established measures.

Furthermore, CFA provides specific statistical indices (detailed below) that quantify the degree of misfit, offering diagnostic information that EFA lacks. If the hypothesized structure does not fit the data well, CFA results can guide model modification, though such post-hoc modifications must be acknowledged as exploratory in subsequent analyses. This difference underscores the maturity of the measurement concept: EFA helps discover the structure, while CFA helps confirm the validity and generalizability of the structure across different populations and contexts.

3. The Role of Model Specification and Identification

Effective implementation of CFA relies heavily on careful model specification. Model specification involves defining the relationships between the observed variables and the latent factors, which includes specifying the factor loadings (the strength of the relationship), the factor variances and covariances, and the error variances (the unique variance in each observed variable not explained by the factor). Each observed variable must have its error term specified, and these errors are typically assumed to be uncorrelated.

A critical technical requirement in CFA is **model identification**. A model is considered identified if there is a unique set of parameter estimates that can reproduce the sample covariance matrix. To achieve identification, the metric of the latent factor must be established. This is typically done in one of two ways: either by fixing the variance of the latent factor to 1.0 (the standardized solution), or by fixing one factor loading associated with that factor to 1.0 (the reference variable method). Without proper identification, the model cannot be estimated reliably, leading to non-convergence or statistically ambiguous results.

When specifying the model, researchers must also consider whether they are pursuing a first-order or a higher-order factor structure. A **first-order CFA** model posits that observed variables load directly onto distinct, correlated factors. A **higher-order CFA** model posits that the correlation among these first-order factors is explained by an even more abstract, underlying second-order (or higher) latent factor. For instance, subscales measuring different facets of anxiety might load onto

a first-order factor, and these first-order factors might then load onto a single second-order factor representing General Anxiety. This nested approach allows for testing complex theoretical hierarchies and provides a more parsimonious explanation for the observed correlations.

4. Key Model Fit Indices

The primary output of CFA is a set of statistics known as model fit indices, which quantify the discrepancy between the observed data and the hypothesized theoretical model. No single index is definitive; researchers typically report a combination of absolute, parsimony-adjusted, and incremental fit indices to provide a comprehensive assessment of the model's acceptability. These indices are essential for concluding whether the hypothesized structure provides a statistically plausible fit to the empirical observations.

The absolute fit indices measure how well the model reproduces the sample covariance matrix. The most fundamental of these is the **Chi-Square Test (χ^2)**. A non-significant Chi-Square value suggests that the implied covariance matrix is not statistically different from the observed covariance matrix, indicating excellent fit. However, Chi-Square is highly sensitive to large sample sizes, often resulting in rejection of models that are otherwise theoretically sound and practically useful. Therefore, supplementary indices are essential. The **Root Mean Square Error of Approximation (RMSEA)** is a popular absolute fit index that assesses the lack of fit relative to the degrees of freedom. Values below 0.06 or 0.08 are generally considered indicative of a good fit.

Incremental fit indices compare the specified model to a baseline model (usually a null model where all observed variables are uncorrelated). These indices assess the proportion of improvement in fit gained by moving from the baseline model to the proposed model. Key examples include the **Comparative Fit Index (CFI)** and the **Tucker-Lewis Index (TLI)**. For both CFI and TLI, values exceeding 0.90, and ideally 0.95, are conventionally accepted as indicating a good fit to the data. Finally, parsimony-adjusted indices, such as the **Standardized Root Mean Square Residual (SRMR)**, provide a measure of the average standardized residual variance between the observed and predicted covariances, with values below 0.08 generally desired.

5. Assumptions and Data Requirements

Like all inferential statistical methods, CFA relies on several underlying statistical assumptions regarding the nature of the data and the measurement error. Violations of these assumptions can lead to biased parameter estimates, inflated standard errors, and unreliable model fit statistics, jeopardizing the validity of the conclusions. Understanding and testing these assumptions is a mandatory step in responsible CFA usage.

The traditional estimation method for CFA is Maximum Likelihood (ML) estimation, which assumes that the observed variables are measured on a continuous scale and that their distributions are

multivariate normal. **Multivariate normality** is the most frequently violated assumption in real-world social science data, where variables are often ordinal (e.g., Likert scales) or show significant skewness and kurtosis. If the data is substantially non-normal, researchers must employ robust estimation methods, such as Maximum Likelihood Robust (MLR) or Weighted Least Squares Mean and Variance adjusted (WLSMV), which are specifically designed to correct for non-normality and categorical data.

Furthermore, CFA requires large sample sizes to achieve adequate statistical power and stable parameter estimates, particularly when models are complex (having many factors or indicators). While there are no universal hard rules, recommendations often suggest a minimum of 200 cases, or a ratio of at least 10 observations per estimated parameter. Finally, observations are assumed to be independent, meaning that the measurement of one individual does not influence the measurement of another. Violation of the independence assumption, often occurring in clustered or longitudinal data, necessitates the use of more complex SEM extensions like multilevel modeling.

6. Applications Across Disciplines

CFA has become an indispensable tool across numerous scientific disciplines due to its rigorous capacity for construct validation. Its primary utility lies in psychometrics, where it is foundational for establishing the validity of measurement instruments. Before any psychological scale--be it for intelligence, anxiety, or job performance--is widely adopted, CFA is used to confirm that the items cluster into the theorized latent constructs consistently. This validation step ensures that the instruments are fit for purpose and that subsequent hypothesis testing is not contaminated by poor measurement quality.

Beyond psychology, CFA is widely applied in marketing and business research to validate scales measuring concepts such as consumer loyalty, brand perception, or organizational culture. For instance, a researcher might hypothesize that customer satisfaction is composed of three latent factors (product quality, service responsiveness, and value perception); CFA would test if the survey items reliably map onto these three factors as specified. In public health and medicine, CFA helps validate instruments used for health status assessment, quality of life scales, and adherence to medical regimes, providing standardized metrics for clinical trials and epidemiological studies.

In sociology and education, CFA is crucial for validating complex theoretical models involving concepts like socio-economic status or academic motivation. It allows researchers to move beyond simple sum scores, providing evidence that the chosen manifest variables are indeed functioning as reliable indicators of the underlying, theoretical constructs. This widespread application across the social and behavioral sciences highlights the technique's significance in ensuring that measurement models are robust before they are used to test complex causal relationships within the broader SEM framework.

7. Advantages and Limitations

The advantages of CFA stem from its theoretical rigor and precision. It provides an explicit, quantitative test of a researcher's measurement theory, offering definitive statistical evidence for construct validity, which is superior to the exploratory nature of EFA. CFA results allow for the comparison of competing theoretical models (e.g., comparing a one-factor structure against a three-factor structure) using nested model comparison tests based on changes in the Chi-Square statistic. Furthermore, CFA is the essential first step in structural equation modeling, as a poorly fitting measurement model (CFA) will inevitably lead to biased results in the overall structural model (SEM). By explicitly accounting for and correcting for measurement error during the estimation process, CFA provides more accurate estimates of the relationships among latent variables.

Despite its strengths, CFA is subject to several limitations. First, its reliance on strong a priori theory means that if the theory is fundamentally flawed, the CFA will fail to fit the data, potentially leading researchers to erroneously modify the model based on statistical indices (e.g., adding correlated errors or cross-loadings) rather than substantive theoretical justification. This practice, known as specification searching or "data snooping," can lead to models that fit the sample data well but are not generalizable to new samples. Ethical statistical practice requires such post-hoc modifications to be cross-validated in a new dataset.

Second, CFA is often sensitive to model misspecification. If an important indicator is omitted, an irrelevant indicator is included, or an incorrect factor structure is imposed, the model fit indices may be poor. Interpreting poor fit is complex: it could mean the theory is wrong, the sampling is inadequate, or the data violates key assumptions like multivariate normality or independence. Finally, the complexity of the statistical software and the inherent requirement for large sample sizes present practical hurdles, particularly for researchers working with small, specialized populations or limited resources.

Further Reading

[Confirmatory factor analysis - Wikipedia](#)

[Structural Equation Modeling - Wikipedia](#)

[Brown, T. A. \(2015\). Confirmatory Factor Analysis for Applied Research. Guilford Publications.](#)

[Schumacker, R. E., & Lomax, R. G. \(2010\). A beginner's guide to structural equation modeling. Routledge.](#)