Validity of Data Collection Instruments in Psychology Using Confirmatory Factor Analysis

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Abstract:
This research aims to address the fundamentals of confirmatory factor analysis. The researcher focused on the methodological and functional aspects of this method, which are often absent or neglected, thereby moving away from the "technical perspective"—that is, focusing solely on the technical aspect, statistical proof, or purely quantitative methods at the expense of the theoretical implications of the scale. This was achieved by clarifying the various semantic and logical aspects of the confirmatory factor analysis method. The researcher divided the process of constructing the factor model to be tested into steps to facilitate understanding, employing, and applying the fundamentals of confirmatory factor analysis, without neglecting structural equation modeling, which is the essence of confirmatory factor analysis. Finally, concluding remarks were presented.
Keywords: Structural equation modeling - Confirmatory factor analysis

Introduction:

Understanding concepts is considered one of the most important processes in all scales. This is due to the imprecision, ambiguity, and confusion associated with many constructs (components) related to the social sciences. Interpreting social phenomena requires developing concepts by operationalizing their indicators, which represent variables. Studying the validity of a concept (variable) requires a logical and empirical approach to the subject. Fundamentally, studying construct validity means studying the validity of the theory underlying the scale or the theory on which the test is based. The internal structure of a data collection instrument is among the sources of evidence for modern validity theory. Therefore, to obtain validity evidence based on the internal structure of measurement instruments, we use factor analysis.

1- Research Problem:

The research problem is summarized in how to verify the factor structure of scales in the psychological, educational, and social sciences (construct validity) using confirmatory factor analysis. The research problem is detailed in the following questions:

1- What is the nature of structural equation modeling?

2- What is the nature of factor models?

3- What are the procedural steps for confirmatory factor analysis in estimating the validity of psychological scales and tests?

2- Importance of the Research:

The importance of the research is reflected in the following:

1- The absence of research, at the level of the Arab world in general and Algeria in particular, targeting the factor structure of scales and tests (confirmatory factor analysis) in the psychological, educational, and social sciences as a methodological approach.
2- The widespread and excessive use of confirmatory factor analysis in doctoral studies, particularly in psychometrics.
3- Failure to observe the scientific methodology required for the proper use of confirmatory factor analysis and its implications.

3- Research Objectives:

The objectives of the study are as follows:
1- To investigate the methodological and functional aspects of confirmatory factor analysis.
2- To review factor models and their types, which serve as a bridge to understanding confirmatory factor analysis.
3- To employ and apply the confirmatory factor analysis method.

4-Research Methodology:

This research is a theoretical and analytical study that differs from other studies in that the researchers used the descriptive method to describe the phenomenon of modeling with structural equations and confirmatory factor analysis, and the logical analysis method through reasoning, analysis, and discussion, because the methodology does not provide certain knowledge that is not open to discussion, but rather provides knowledge that is open to critical review.(1)

Structural equation modeling: It is a set of advanced statistical methods or strategies in data analysis aimed at testing the validity of the network of relationships between variables (theoretical models) assumed by the researcher as a whole, without needing to break the hypothesized relationships into parts and test the validity of each part separately. Testing the validity of the hypothesized relationships in the model between variables or concepts as a whole, without dissecting or dividing them into partial relationships, provides the researcher with a more accurate picture of the variables' actual behavior. The complexity of reality makes it impossible to extract simple parts from the fabric of relationships between variables, such as studying the correlation between two variables or studying differences (which is the prevailing and dominant approach in the nature of theorizing and hypotheses presented in research); this provides the researcher with mosaic-like, truncated, and abridged results that may not reflect the actual behavior of variables in reality.(2)

The structural equation-based analysis strategy for testing theoretical models is characterized by the following features:
1- Structural equations are used to test the relationships between variables from a confirmatory or verifiable perspective, not from an exploratory or exploratory perspective.
2- Structural equations aim to test the validity of models that mostly involve relationships between underlying variables.
3- Traditional primary and advanced multivariate statistical methods such as multiple regression analysis, multivariate analysis of variance, etc., are based on the assumption that the independent variables used in the analysis do not involve measurement error. However, the structural equation is different, as the variables are included in the analysis with all the variance they contain, including the variance caused by measurement error.
1- The structural equation – unlike other advanced statistical methods – enables the modeling of errors or variances of measured variables or indicators that are preferred over covariance (the

relationship of the indicator or measured variable to its latent variable or factor), assuming the existence of a correlation or variance relationship between some errors of the indicators.

2- The information used to test the validity of the model does not take the form of raw data (the columns indicate the observed or measured variables or indicators, and the rows indicate the individuals), but rather takes the form of a variance matrix, or for short, a covariance matrix.

3- Structural equation modeling is a powerful, flexible, and comprehensive set of statistical techniques that can be considered comparable to some traditional advanced statistical methods such as multiple regression analysis and correlation.Group analysis, or analysis of two sets of variables, and analysis of multiple covariance and analysis of multiple variance are special cases of structural equations.

There are currently flexible and good statistical packages specifically for structural equations, the most important of which areLISREL-EQS-AMOS-Mplus—(2)

5–The model:

The term “model” has acquired broad methodological connotations, referring to all forms and products employed to serve the aims of knowledge. Wirmus (1983) tends to exclude the direct relationship that might be assumed to arise between the model and the real-world domain, since what particularly distinguishes a model is that it is a construct generally formulated from certain properties selected from reality. This is done on the basis of a pre-existing theory, which may be naïve. Similarly, formal thought substitutes for it a certain conceptual framework derived from languages and other symbolic components, thereby establishing diverse systems with immense expressive power. It is a representation of, or a simulation of, a phenomenon. Some consider a model to be an artificial symbolic expression or conception of a situation or problem, helping to achieve sound understanding as a basis for making an appropriate decision. (3)

The model usually involves a number of relationships between variables, and therefore it goes beyond the simplicity of differential and correlational hypotheses that may not accurately reflect the behavior of variables in reality. The model usually aims to approximate the reality of the relationships between the studied variables, attempting to match the behavior of the targeted variables, and reflecting as much as possible the network of relationships between the studied variables, which often goes beyond the difference or mere correlation between two variables, without being excessive in mentioning details or including unimportant variables in the model, and without excluding the study of important variables, or neglecting some of them due to a lack of awareness of their importance in the model.(4)

To illustrate the importance and advantages of model-based theorizing, we present its superiority over hypotheses:

1- Matching the behavior of the complex and intertwined variables in reality, something that hypotheses cannot do.

2- The flexibility of the model in theorizing, as the same variables may play different roles, sometimes as independent variables, sometimes as mediating variables, and sometimes as dependent variables. This is not found in hypotheses.

3- Testing the fabric of relationships involved all at once. Hypotheses, on the other hand, break them down.

The overall goal of structural equation modeling is to determine the extent to which a theoretical model matches field data, i.e., the degree to which the theoretical model is supported by the sample data. If the sample data supports the theoretical model, then more complex theoretical models can be proposed. If the data does not support the theoretical model, then either the original model is modified and tested, or other theoretical models are developed and tested. Structural equation model:

It is a hypothetical pattern of direct and indirect linear relationships between a set of latent and observed variables, or it is a complete path model of the relationship between a setVariables can be described or represented in the form of a graph (3)

Modeling language:

It is preferable to support the theoretical model or illustrate it with diagrams.Diagrammatically, Figure 1 is an example of an illustrative diagram. There is a standardized language for modeling agreed upon by scientists, consisting of a set of shapes and arrows used in drawing the model (a general consensus on the use of the following shapes).

Latent variable size (5)

The double-headed convex arrow symbolizes the mere correlation or incompatibility between two independent variables.

A straight arrow with a single point or direction symbolizes the relationship between two variables, which is usually either a causal or predictive relationship. It is sometimes called a path coefficient, path coefficients, or simply paths.

The rectangular or square shape symbolizes the observed variable, the measured variable, or the latent variable.

The oval or circular shape symbolizes the latent variables.

Before we discuss confirmatory factor analysis, it is advisable to discuss the types of theoretical models: 1- Structural models.

2-Path analysis models.

3- Factorial models.

Types of theoretical models

These represent the most important modeling patterns. A researcher's understanding of these three patterns is a necessary prerequisite for understanding the modeling methodology.(**6**).

These latter models (factorial models) are what concern us in our research because confirmatory factor analysis is one of their types.

Factorial models:

Factorial models differ from constructivist models and path analysis in that the latter two models involve causal or predictive relationships between variables or underlying factors if the model is constructivist, or between measured variables if the model is path analysis. Factorial models, in their various forms, do not study relationships between two or more different variables; rather, they are analytical models. This is because they are primarily concerned with analyzing a specific concept or variable into the dimensions or factors that are assumed to constitute the substance or structure of the concept. In other words, the researcher assumes that the concept has a structure, and assumes that this structure consists of one, two, or several components. There are two types of factorial models—(2)

The exploratory factorial model and the confirmatory factorial model:

1- The exploratory factor model:

In this model, the researcher lacksA clear understanding of the concept structure is needed before conducting exploratory factor analysis, as the number of factors is often not determined, nor are the nature and names of the factors defined, nor is it specified which measured indicators, variables, or items are saturated on a particular factor rather than the others. The researcher lacks a clear understanding of the saturation pattern. Therefore, we say that the researcher may initially believe that the concept under study may involve a number of factors or dimensions, but lacks a clear understanding of the number of these factors and their nature.

2- The assertive factorial model:

Confirmatory factorial models – in contrast to exploratory factorial models – are based on a clear theoretical framework under which the researcher can propose a factorial model that includes all the information.

Three types of confirmatory factor analysis can be distinguished:

- Confirmatory factor analysis, single-factor or dimensional (homogeneous).
- Confirmatory factor analysis consisting of two or more factors, multifactor analysis, or ordinary confirmatory factor analysis, is also called non-hierarchical confirmatory factor analysis or first-order confirmatory factor analysis.
- Hierarchical factor analysis or second-order factor analysis will be discussed below:

1- The one-dimensional assertive factorial model or factor:

In it, the researcher assumes that a certain concept involves a single factor such that the items, questions, or scales (i.e., the measured variables or indicators) share sufficiently in this concept. That is, the common denominator between the measured variables or indicators indicates a single factor or dimension that summarizes the concept to be analyzed. The area of common relationship between the indicators and the measured variables, whether they are items, scales, or otherwise, represents the theoretical significance of the concept. Since the indicators or measured variables meet at a single concept, it is called a one-dimensional or homogeneous hypothetical concept, term, or construct.

One-dimensional confirmatory factor model or factor

From the above, we can conclude the following:

Firstly – the one-dimensional assertive factorial model is based on the assumption that the concept involves one dimension or factor.

Secondly, this single factor is indicated by several indicators rather than just one. It is recommended that there be at least three indicators. Therefore, the factor is measured indirectly through these indicators.

Thirdly - The underlying factor or variable is the one that affects the measured indicators or variables. In other words, it is the one that gives meaning and significance to the function or purpose of the measured indicator or variable, whether these indicators are items, tests, scales, or other.

2- The two-factor or multifactor assertive factorial model, or the first-order ordinary assertive factorial model:

This model – unlike the one-factor or one-dimensional model – is based on the assumption that there is more than one factor (two or more factors) to represent or comprehend the structure of the concept under study or analysis.

3- The hierarchical or second-order assertive factor model:

The assumption of a second-order factor model is considered an advanced stage in theorizing. Because the researcher was guided to the concept of a hierarchical structure among the underlying factors, he assumed the existence of a comprehensive underlying factor (a second-order factor) and sub-underlying factors to it (first-order underlying factors). Therefore, he did not assume the existence of correlations or relationships of variation (or correlations between first-order factors).

Before discussing confirmatory factor analysis and its procedural steps, let's briefly touch on factor analysis.

The concept of factor analysis:

It is a statistical method that aims to interpret positive correlations—those with statistical significance—between different variables. In other words, factor analysis is a mathematical process that aims to simplify the correlations between the various variables included in the analysis, arriving at the common factors that describe and explain the relationship between these variables. Factor analysis is a statistical method for analyzing multiple data sets that are linked to each other with varying degrees of correlation, summarizing them into independent classifications based on qualitative classification criteria. The researcher then examines these classification criteria and infers the common characteristics between them according to the theoretical framework and scientific logic with which he began.**7)**

Factor analysis seeksTo uncover a relatively small number of unobserved (or underlying or latent) variables that adequately represent the interrelationships between a large number of measured (or observed, noted, or apparent) variables, such that each latent variable represents a quantity of shared variance (information) between a number of measured variables, or represents the common denominator of information shared by a set of observed or measured variables. This facilitates dealing with numerous variables through a small number of underlying variables that represent the apparent variables in all their multiplicity and diversity. This allows scientific studies to focus strongly on the important (latent) variables, and the study is not scattered among a large number of apparent variables that contain a large amount of repeated information despite their apparent differences. These few underlying or implicit variables that summarize most of the information contained in the numerous measured apparent variables are technically called underlying factors or factors for short.**2**)

The worker: It is a latent variable, but it differs from variables in that most variables can be measured directly, whereas factors are hypothetical variables derived from the analysis of data from a set of variables that have been directly measured.

- The measured, apparent, or observed variables:

This refers to the elements that are subject to factor analysis. These elements or variables may be questionnaire items, test items, or scales, where each item represents a variable. They may also be subscales of a primary scale, where each subscale is considered a variable. Alternatively, the variables may be complete scales rather than subscales or items, in which case the aim is to uncover the underlying factors common to what these scales measure.**2**)

The concept of confirmatory factor analysisConfirmatory Factor Analysis

Another name for confirmatory factor analysis is (measurement model), and it represents the second statistical technique for structural equation modeling that deals specifically with measurement models, that is, it is concerned with studying the relationships between indicators (items, scores, values from scientific observations of behavior, etc.) and underlying variables or factors, that is, it deals specifically with scales and questionnaires.**3**.)

The difference between confirmatory factor analysis and exploratory factor analysis:

The differences are almost the same as those we mentioned when comparing exploratory and confirmatory factor models, but we will focus on the fundamental difference. The fundamental difference between them is that confirmatory factor analysis is used to test the theoretical model on a confirmatory basis to verify the model's validity and reliability, while exploratory factor analysis is used to extract the underlying factors of the measured variables in an exploratory way; that is, the underlying factors of the measured variables are identified after the analysis. (4).

Objectives of confirmatory factor analysis:-Studying the relationships between underlying factors, the indicators that represent them, and the factors among themselves.-Providing evidence of construct validity for the scale

Evidence of construct validity: The evidence for construct validity consists of convergent validity and convergent validity.AYazi

-First, convergent truth: It refers to the assumption that a group of items represents the same factor if the correlation ratio is high. This means that the items of the factor represent the same factor in the case of high correlation and do not represent another factor.

Secondly, complete honestyAYazi This refers to the assumption that a set of items does not represent the factor if the correlation ratio is weak.**2)**

Some of the steps a researcher takes before conducting confirmatory factor analysis:

*<u>Before conducting confirmatory factor analysis, the researcher must necessarily define their theoretical factor model precisely, based on their theoretical grounding of the subject. The following dimensions of the factor model are required:</u>

1- Determines the type of factorial model, including the number of factors: Is the factorial model unifactor, bifactor, or multifactor?
2- It identifies the variables that are measured or the indicators (whether items, subscales, tests, etc.) that measure each of the assumed factors. In other words, the researcher imagines that the subject consists of a factor structure containing one or two factors, and that each factor specifically contains three or four indicators that measure it accurately.
3- It determines whether the factors identified are related or independent. Often, the researcher assumes that the factors identified are related.
4- Measurement errors are defined as the remaining variance that the factor cannot explain for each of its measured indicators. These errors consist of random errors and systematic errors (the researcher assumes beforehand that the measurement errors of the factor indicators are random and independent, or that some of them are not independent. He identifies which measurement errors of the indicators he believes are related. Assuming a correlation of some measurement errors in a factor model based on a strong theoretical foundation increases the ability of the factor model to fit the data and its ability to explain.)**2**)

**<u>Steps for confirmatory factor model testing (confirmatory factor analysis procedures):</u>

References differ in specifying the steps for testing the quality of conformity of the theoretical model developed by the researcher, whether it is a factorial model.

Is it a structural model, or a path analysis model? Despite the significant differences in determining the number of steps and in explaining the nature of each step, we tend to adopt the classification adopted by Professor Tighza.

He summarized the process of testing the assumed theoretical model when employing the confirmatory factor analysis method in five basic stages (with an explanation of the nature of each stage):

Phase One: Building and Defining the Model SPECIFICATION

1-Definition:

This involves model building or definition, which entails employing appropriate theories, theoretical frameworks, and theoretical models, and the researcher's ability to theorize in developing a factorial theoretical model. This is essential. Reinforcing the modeling process with a diagram enhances clarity, facilitates the use of language, symbols, and equations, and adds an aesthetic touch to the model. It also organizes theoretical considerations and helps translate the diagram into specialized statistical software languages for structural equation modeling (such as the LESERL instruction language and the AMOS package), which are among the most popular packages for structural equation modeling. Factorial models are often susceptible to certain designation errors, the most significant of which is the absence of one or two crucial variables whose importance the researcher overlooked, and therefore their omission from the model. Alternatively, the model may suffer from an excess of variables that do not perform a specific function within the model, or may even obscure or hinder the role of critical variables. Designation errors pose a significant threat to the model's validity, impede its ability to fit, amplify bias, and increase measurement errors and unexplained variance errors.

Through this, the researcher has completed the step of developing or defining the hypothetical model..

After the theoretical definition of the model and before moving on to estimating its parameters, the issue of model assignment must be addressed.

2- The second stage: Assignment: Assigning the modelidentification

Assignment refers to identifying or estimating the needs of the hypothetical model and comparing them to the non-repeating units of information in the data (the information available in the data). This step concerns the extent to which sufficient information is available in the sample data to arrive at a single, specific solution for the free parameters of the hypothetical factorial model. If the model lacks assignment, for example, it becomes impossible to estimate a single, specific value for each of the free parameters of the hypothetical model. Each parameter will have a large number of values that represent a solution for it, and therefore it becomes impossible to select the most appropriate solution for each parameter.

But when is a given model characterized by specificity? And in order to know how to classify the model as transcendental, saturated (specific), or indeterminate, we must know the following:

A-We learn about the method that enables us to count the number of free parameters for the assumed factorial model.

B-We learn about the method that enables us to count (or enumerate) the number of non-repeating elements in the variance and covariance matrix of the sample.

The free parameters that need to be estimated in the confirmatory factorial model are:

1- The number of variance values for the underlying factors if they are free and not restricted to a specific value.
2- Number of errors in measuring indicators.
3- Variation or correlation between underlying factors.
4- The number of saturations of the measured indicators on their underlying factors.
5- The correlation between measurement errors (sometimes assumed by the researcher)
6- Variance of dependent variables. (These are not considered free parameters)

Therefore, the variance and covariance of the independent variables (latent factors, measurement errors, and residuals) and saturations (the relationship between a factor and its indicators) are considered free parameters unless they are restricted (fixed) to a specific fixed value to define the unit of measurement for the latent variables (factors, measurement errors, or residuals). However, the variance of the dependent variables (not the independent variables) is not considered a free parameter. In short, the model's requirements are expressed as the number of units of information the model needs to estimate its parameters. Parameters are defined as anything not restricted to a fixed value that the program calculates. The number of model parameters that need to be estimated beforehand can be determined using the AMOS package or any other package designed for this purpose.

The model's needs can be briefly estimated as follows:

First - Calculating the number of variances for the independent variables, whether measured or latent.

Second - The number of correlations or variances between the measured or latent factors or variables (number of convex arrows)

Thirdly - the number of unrestricted paths (straight, one-way arrows).

b) The method that enables us to count (or enumerate) the number of non-repeating elements in the variance and covariance matrix of the sample is:

Number of variables or indicators measured × [Number of variables or indicators measured + 1]/2

After we count the number of free parameters in the model, which represent the amount of information the model needs to test its validity, we determine the amount of non-recurring or available information in the empirical data.

We compare the model's needs with the non-repeating units of information available in the data. We then proceed to calculate the degrees of freedom to determine the model's assignment type. Ideally, the model should be trans-assigned, meaning the degrees of freedom are positive. Note that the degrees of freedom are negative for an unassigned model and zero for a saturated model. To determine whether the number of degrees of freedom is negative (indicating an unassigned model), zero (indicating a saturated model), or positive (indicating a trans-assigned model), we subtract the number of free parameters enumerated in the theoretical model from the number of non-repeating elements in the variance matrix of the sample (the number of units of information available in the sample data). In other words, we use the simple relationship:

Number of degrees of freedom = Number of non-repeating values for the variance and covariance of the measured or sampled index matrix.

The number of free parameters for the assumed model.

Firstly-Lack of appointmentUnder-identified (or simply unidentified)

secondly-The situation where the available data units are equal to the number of free parameters required by the model is called a saturated model.Saturated Just-identified

The match with the data is complete. This situation is preferable to avoid, although it is positive, as it lacks economy in theorizing, or an excess of relationships (economy in the number of parameters that need to be estimated as a result of the abundance of relationships).

Thirdly -The model's needs (number of free parameters) are less than what is available in the data.

This is the optimal situation, and the model in this case is called a denotative or trans-denotative model.Over-identified overidentified Determining a unit of measurement for latent variables. The

second thing in this second stage is determining a unit of measurement for the model variables because the variables used are concepts that lack a unit of measurement, and the unit of measurement for these concepts or latent factors is determined in two ways:
-Fixing one of the saturations on the factor with a fixed value (value one)
– Fixing the variance of the factor with a constant value equal to one instead of fixing one of its saturations

Third stage: Method for estimating free parameters: Estimation

The maximum probability method of estimation aims to find numerical values for these free parameters in the model such that the data matrix derived from the model (the variance matrix of the hypothetical model) is very close to the sample data, i.e., to the variance matrix of the sample, which represents the reference frame that the hypothetical model should accurately reproduce in order to be a theoretical model that matches the sample data. The goal of estimating the values of the free parameters of the hypothetical model is to achieve the greatest possible reduction in the differences between the values of the elements of the variance matrix of the sample. The smaller the difference between them, the closer the model comes to representing the sample data. This method (the numerical mathematical method) is called fitting or matching functions. These methods differ according to the method of parameter estimation, with each estimation method having its own specific fitting function. Specialized statistical packages provide several methods for estimation:

Maximum probability method: It is based on a set of assumptions, which are:

1- The eye size should be large.
2- The model's indicators must have a continuous measurement level (i.e., be interval or relative).
3- The distribution of scores of the measured indicators in the model should have a moderate multiple distributions, noting that if there is a slight deviation, it does not affect the accuracy of the estimates made by the maximum probability function. Given the importance of the characteristics of the maximum probability method, some specialists recommend using this method in all cases.

If some of the assumptions of this method are not available in the data, the results of other alternative estimation methods can be used. The researcher includes in his report a summary of the results of the alternative estimation methods in case they differ from or contradict the results of the maximum probability method.

It should be noted that the default parameter estimation method used by most specialized packages (unless the user specifies another method) is, by default or automatically, the maximum probability method. This method provides its user with accurate estimates of the model parameters when the data has the property of multiple normality, and it maintains the accuracy of its performance (parameter estimates) even in the case of a moderate degree of deviation between the distribution of scores and the normal distribution.

After learning about the methods of estimating the model parameters, it is necessary in the next step to learn about the conformity indicators, meaning whether the assumed model, which consists of the relationships that were measured and estimated, represents the sample data and therefore has a good conformity to the data or information obtained in the research, or does it not represent the study sample data, which indicates that the assumed model is incorrect?

Phase Four: Testing the conformity quality of the model using conformity indicators .testing

Matching refers to the extent to which a model can utilize all the information contained in the original data, or the degree to which the model can represent the sample data without deviating significantly from it. Therefore, numerous indicators have been proposed for assessing matching, and several classifications exist.

Perhaps the most widely used and common classification is the one that divides the conformity indicators according to their differences.

They are divided into three major categories or groups:

Group 1: Absolute Match Indicators Absolute Fit indices

It is called absolute because it is not based on comparing the conformity of the assumed model with other restricted models.

Group Two: Comparative Fit Indices / Incremental Fit Indices

These are the indicators that estimate the relative improvement in fit of the hypothetical model (the researcher's model) compared to a baseline model. Baseline model: The baseline model is mostly represented by the model with independent variables, and is called, for short, the Independent Model or the Null model, which is based on the assumption that the variances of the variables observed at the population level are equal to zero or zero, and only the values of the variance of these variables remain.

Third group: Indicators for correcting the deficit in the economy Parsimony Correction Indices or Economic Indicators

These indicators differ from the chi-squared indicator and the root mean squared standard remainders indicator (SRMR) and others involve a penalty function when free parameters are added to the model without any benefit, i.e., without any improvement in the model's conformance. This situation is called poor parsimony or a lack of economy in the free parameters that need to be estimated.

Fifth stage: Modifying the modelmodification:

To examine defects in specific locations within the assumed model, or a defect in a part or element (which may be a relationship, parameter, or other element) of the model, there are two methods: - the residuals examination method - and the adjustment indicators examination method, which are provided by all statistical packages.(**2**)

The model is modified for several reasons, including:

Some paths or relationships between errors or between the factor and the measured indicators may increase the model's ability to explain and therefore its ability to match, and therefore they are added in light of the adjustment indicators to be estimated in the modified model.

Some of the residuals between the sample data matrix (the covariance matrix between the measured variables) and the model-derived data matrix are large, indicating a divergence between the two matrices in some parameters.

Some relationships are not significant, whether they relate to the variance of error of the observed indicators, or the overloads, which may be significant but of low intensity, and may sometimes be deleted.

Conclusion:

The absence, or rarity, of discussion of models in systematic authorship, or in systematic scientific articles in the social sciences, is what prompted us to address this research topic (confirmatory factor analysis), which is one of the modern statistical methods for data analysis. Research practice in various fields has increasingly tended toward formulating models, or toward formulating models and the hypotheses derived from them. This growing trend toward employing models in research practice may stem from an awareness of the importance of models in framing the research problem. To advance research in the social sciences, many complex problems concerning the use of statistical methods must be resolved. The dichotomy between reliability, on the one hand, and validity, on the other, is no longer applicable. Rather, reliability is now viewed as a source of evidence, like other sources of validity evidence (the modern theory of validity).

Confirmatory factor analysis is considered a modern, advanced method for verifying the factorial construct validity of scales within the framework of structural equation modeling. This is manifested in the process of testing the model by quantitatively evaluating the extent to which scales and tests are suitable and valid. Accordingly, the confirmatory factor analysis model makes major contributions to understanding the hypothetical constructs measured by various tests. It represents a new logic and a new methodology, unlike the previous competing fields of knowledge and methodologies. It is not an aggregative methodology combining several known elements, but rather a new approach to testing that does not rely on statistical significance and uses a set of evidence provided by numerous and diverse fit indices.

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