Fundamentals of Structural Equation Modeling (SEM)

Leila BEKKOUCHE[1], Rim KASMI[2]
[12]University of 8 May 1945, Guelma, Algeria.
[1]Email: bekkouche.leila@univ-guelma.dz
[2]Email: rim.kasmi@univ-guelma.dz

Received :15/07/2025 ; Accepted :03/02/2026 ; Published :06/04/2026

Abstract

The use of Structural Equation Modeling (SEM) in the humanities and social sciences has become an essential and indispensable approach that must be adopted in future field research, particularly in psychology. This shift comes after moving beyond the traditional reliance on complex and multiple hypotheses that demand considerable time and effort from researchers, while often failing to fully capture or control all variables influencing the phenomenon under study. In contrast, structural modeling enables the simultaneous examination of a large and complex set of interrelated relationships, while also accounting—at least partially—for measurement errors in the observed variables.

Given the importance of this modern statistical approach, the aim of this article is to present clear analytical concepts regarding Structural Equation Modeling (SEM), its objectives, key advantages, fundamental principles, and the most commonly used model types. This will be supported by practical examples and applied research models to enhance understanding.
Keywords: Model, Measurement Model, Structural Model, Latent Variable Model

Introduction

Philosophers were the first to discuss the observed temporal regularity of events, which formed one of the most important foundations for addressing the causality of phenomena and how they occur. Among the earliest theories in this regard was David Hume's theory, which posited that cause and effect occur together at the appropriate time, that the cause must precede the observation of the effect, and that the cause cannot occur without the effect being present. Thus, the cause is inferred from the effect. However, statistical methods—whether classical or advanced—have shown that covariance between variables alone is insufficient to establish causality. This limitation can be attributed to two main issues: first, the problem of the third variable (confounding), and second, determining the direction of causality.

For example, a strong correlation may be observed between learning motivation and academic achievement; yet it is unlikely that motivation alone causes achievement. It is more plausible that an external factor (or factors) influences both variables. John Stuart Mill (1865) outlined three necessary conditions for inferring causality: (1) the cause must precede the effect, (2) the cause and effect must be correlated, and (3) all alternative explanations for the relationship must be ruled out.

According to researchers, causal relationships refer to cause-and-effect connections between events or behaviors and their potential outcomes (Sanchez & Heene, 1997, p. 4). In many respects, John Stuart Mill owes a significant intellectual debt to David Hume, as the first two conditions reflect Hume's criteria of association and temporal precedence. Mill's primary contribution was the addition of the third condition, which emphasizes the need to exclude the effects of a "third variable." To verify this third criterion, Mill proposed several methods: the method of agreement (the effect occurs when the cause is present), the method of difference (the effect is absent when the cause is absent), and the method of concomitant variation (when the above relationships are observed, causal inference becomes stronger because most alternative explanations are eliminated).

The first approach allows for causal inferences because potential causes are compared systematically (i.e., the situation in which the cause is present is compared with the situation in which it is absent). In contrast, the latter approach does not involve such manipulation of the cause; therefore, causality cannot be inferred. For instance, we may observe that night always follows day, but this does not necessarily mean that day causes night (Hume). Hence, in situations where the cause cannot be experimentally manipulated, we cannot provide causal prescriptions regarding our variables. Statistically, this implies that when analyzing data from non-experimental settings, we cannot draw any conclusions about causation.

The emergence of Structural Equation Modeling (SEM)—also known as covariance structure modeling—represents an attempt to provide a flexible framework for constructing causal models. SEM is considered one of the modern approaches that have significantly contributed to the advancement of research methodologies in the social sciences.

Structural Equation Modeling (SEM) has become a core component of advanced multivariate statistical analyses that involve more than one dependent variable, such as multivariate analysis of variance (MANOVA), discriminant analysis, cluster analysis, and factor analysis. Its use has been steadily increasing in educational, psychological, and social sciences research. Although SEM first appeared in the early 1970s through the work of Jöreskog (1969) and others, it only gained widespread popularity and adoption among researchers toward the end of the 20th century. In the research literature, it has been referred to by various names, including: structural equation modeling, covariance structure modeling (CSM), covariance structure analysis, causal modeling among latent variables, latent variable analysis, simultaneous equation modeling, and structural modeling. Some scholars also refer to it as causal model analysis, structural equation analysis, or path modeling (Al-Sayed Amer, 2018, pp. 13–14).

Structural Equation Modeling is an attempt to model causal relationships between variables by incorporating all relevant variables involved in studying the phenomenon. This methodology relies on "representing the studied phenomenon and the relationships among its elements (variables) through a model that simulates reality. It simplifies and symbolically depicts (via graphical representation) an artificial construct of a given situation or problem in a way that facilitates clear conceptualization as a basis for sound decision-making" (Shaker, 2007, p. 207).

Accordingly, a Structural Equation Model allows for the clarification of direct and indirect linear relationships among a set of latent and observed variables. It also enables the examination of the full network of relationships and correlations among multiple variables of the phenomenon through a graphical path diagram. This diagram represents a visual depiction of the general linear model, which encompasses multiple regression, and serves as a translation of a series of hypothesized cause-and-effect relationships among a group of variables (Al-Hindawi, 2007, p. 12).

To illustrate the above, we present a clarifying example of a causal path model concerning the effect of medication on behavior. Suppose we wish to test the impact of a drug on certain psychological disorders, such as obsessive-compulsive disorder (OCD). It is evident that checking behavior sometimes characterizes this disorder. Thus, we could take a baseline measure of checking behavior and administer the medication, then re-measure checking behavior to verify whether it has decreased. We might find a strong correlation between medication dosage and the reduction in checking behavior among patients. However, several problems arise in this correlational study. First, the relationship is non-directional: although medication dosage may reduce checking behavior, the severity of the behavior may also determine the dosage (higher doses are typically prescribed for more severe cases). Second, the medication may not have a direct effect on the behavior; rather, it may inhibit certain cognitive processes, which in turn reduce the behavior. Thus, while the effect may be causal, it forms part of a chain of events. Finally, the medication may have no effect at all; both dosage and behavior may be influenced by a third variable. For example, the personality trait of "self-control" may reduce the frequency with which obsessive thoughts translate into actual behavior and may also affect the severity of symptoms reported to the psychiatrist, thereby influencing the prescribed dosage.

What is meant by Structural Equation Modeling?

1. The Concept of Structural Equation Modeling

Definitions of Structural Equation Modeling (SEM) vary widely and sometimes overlap. Some scholars view it as a single statistical technique, whereas in reality it constitutes an integrated set of statistical methods that together form a comprehensive framework known as structural equation modeling. Well-known statistical techniques such as analysis of variance, regression analysis, path analysis, and exploratory factor analysis, when applied in isolation, do not constitute structural equation modeling. However, when these techniques are integrated and work in concert, they collectively form the process referred to as structural equation modeling.

Despite the variation and lack of a single unified definition, we will examine and analyze the most common and closely related conceptualizations to arrive at an approximate understanding. We begin with the definition that regards structural equation modeling as path analysis using latent variables (Latent Variables). It is also frequently referred to as causal modeling—a term historically associated with the statistical method known as path analysis (Amhamed Taghza, 2011, p. 114).

Structural modeling aims to investigate causal relationships and is often used synonymously with causal modeling. Consequently, regression analysis, path analysis, and factor analysis are, by their nature, forms of structural modeling (Al-Sayed Amer, 2018, p. 7). Yasser Al-Mahdi supports this view by describing structural equation modeling as a hypothesized pattern of direct and indirect linear relationships among a set of latent and observed variables. It represents a complete path model of the relationships among a group of variables that can be described or represented graphically. SEM is an extension of the general linear model, enabling the researcher to test a set of regression equations simultaneously (Al-Mahdi, 2007, p. 19).

Anderson and Black (1998) provide further elaboration, stating that structural equation modeling is a statistical technique that allows for the simultaneous analysis of a set of structural equations in which a variable may be independent in one equation and dependent in another (Anderson & Black, 1998, p. 411).

This is corroborated by Ullman and Bentler (2013), who describe SEM as a collection of statistical methods that permit the examination of relationships between one or more independent variables (continuous or discrete) and one or more dependent variables (continuous or discrete), where both independent and dependent variables can be either measured or latent (Al-Sayed Amer, 2018, p. 16).

Taghza adds that structural equation modeling comprises a set of advanced statistical methods and strategies for data analysis aimed at testing the validity of the network of relationships (theoretical models) hypothesized by the researcher as a whole, without the need to fragment these hypothesized relationships into separate parts and test each one individually. Testing the validity of the hypothesized relationships among variables or concepts as an integrated whole—rather than in isolated segments—provides the researcher with a more accurate picture of the actual behavior of the variables (Taghza, 2011, p. 114).

It can also be argued that structural equation modeling provides an estimate of the strength of the hypothesized relationships between variables as specified in a pre-defined model grounded in a coherent theory. It supplies information about the hypothesized effects—whether direct (from one variable to another) or indirect (from one variable to another through a third mediating variable) (Al-Sayed Amer, 2018, p. 15).

According to Schumacker and colleagues, the primary objective of structural equation modeling is to determine the degree of fit between the theoretical model and the empirical data; that is, the extent to which the theoretical model is supported by the sample data (Schumacker et al., 2004, p. 7).

Hershberger and colleagues (2003) define it more broadly as a research methodology used to estimate, analyze, and test models that specify relationships among variables (Hershberger et al., 2003, p. 3).

In a wider sense, structural equation models represent translations of a series of hypothesized cause-and-effect relationships among a group of variables (Al-Qahwaji & Abu Awwad, 2018, p. 13).

Thus, structural equation modeling can be understood as an interconnected and coherent set of statistical methods—or an advanced statistical strategy—whose aim is to analyze data in order to identify and describe relationships between observed variables (Observed or Manifest Variables) and latent variables (Latent Variables) within various structural forms of theoretical models. For example, creative thinking is an abstract concept composed of three dimensions: originality, flexibility, and fluency. Each dimension is measured through a set of indicators (items) that represent the aspects constituting that dimension.

These statistical methods are characterized by flexibility, statistical power, and comprehensiveness. For instance, certain advanced statistical techniques such as multiple regression are considered special or partial cases of structural equation modeling. Moreover, SEM allows for the modeling of measurement errors by assuming, for example, correlations among the errors of certain indicators.

2. Advantages of Structural Equation Modeling

Structural equation modeling is distinguished from other statistical analyses of variables by several key characteristics, including the following:

- It focuses on examining both direct and indirect relationships by integrating multiple advanced statistical techniques.
- It deals with both latent variables and observed (manifest) variables within the structural framework of the hypothesized or proposed theoretical model.
- It enables the researcher to test all the complex and interrelated relationships that constitute the model simultaneously. This feature elevates structural modeling as a distinctive, integrated strategy compared to other statistical methods.
- It takes into account errors in the measured indicators (measurement error and prediction error), which enhances measurement precision by isolating the indicator from measurement error.

Taghza (2018) highlighted several additional characteristics of structural modeling:

- It is used to test relationships between variables from a confirmatory rather than an exploratory perspective. This means the researcher performs statistical analysis on the data only after constructing the theoretical model, in order to verify the fit between the collected data and the hypothesized model. This contrasts with the exploratory approach, in which the researcher does not know the number or nature of the factors until after conducting exploratory factor analysis.
- Structural modeling aims to test the validity of a model that typically involves relationships among latent variables. Latent variables are abstract concepts that cannot be measured directly and are instead assessed through a number of observable, measurable indicators, which may take the form of questionnaire items, dimensions, or scales.
- Traditional statistical methods assume that independent variables are free from measurement error. Consequently, these variables enter the analysis with their full variance, including variance attributable to measurement error. In contrast, structural equation modeling purifies the latent variables from measurement errors (Measurement Error) or residuals.
- The information used to test the validity of the model takes the form of a variance-covariance matrix, in which the observed variables constitute the rows and columns (Al-Sayed Amer, 2018, p. 14).

Byrne (2001) compared structural equation modeling with other multivariate statistical methods and identified five distinguishing characteristics:

- Structural equation modeling adopts a confirmatory (theory-driven) approach to data analysis by specifying the relationships among variables in advance, in contrast to an exploratory approach.

- It provides an explicit estimate of error variance parameters, which, for example, is not achieved in regression analysis that tends to ignore potential error in the dependent variables.
- In traditional analysis, psychometric properties are first verified, followed by hypothesis testing. In structural equation modeling, however, measurement and the structural model are tested simultaneously, allowing the researcher to determine the magnitude of error and its impact on model fit. In other words, both the measurement quality and the hypothesized relationships are examined at once.
  Important Note: In practice, measurement is sometimes tested first, followed by the structural relationships, to ensure the quality of the measurement before examining the relationships among variables in the model.
- Structural equation modeling procedures integrate both observed and latent variables, whereas other statistical methods deal exclusively with observed variables.
- SEM procedures are capable of modeling complex multivariate relationships and estimating both direct and indirect effects of the research variables (Byrne, 2001, p. 125).

Abdul Nasser Amer (2018) adds further distinctive features of structural equation modeling:

- SEM relies less heavily on statistical significance testing compared to other methods such as ANOVA or multiple regression. This is because it evaluates the model as a whole and typically requires large sample sizes. Consequently, the chi-square (χ^2) test, which is commonly used to assess model fit, tends to yield statistically significant results in most cases and is therefore not relied upon exclusively when judging model fit. As a result, tests of statistical significance in SEM do not carry the same weight as in classical statistical testing.
- The SEM strategy surpasses classical methods in its ability to examine mediating variables that simultaneously serve as both independent and dependent variables, while also revealing direct, indirect, and total effects (a capability also present in path analysis).
- SEM excels over classical methods in its capacity to investigate the underlying structures of psychological concepts in relation to the measured variables that constitute them. This aligns well with human and behavioral phenomena, unlike classical methods that deal only with measured variables without addressing the underlying structure of the phenomenon.
- SEM is superior in its ability to detect model misspecification.
- SEM is distinguished by its advanced applications for handling complex models, such as longitudinal data analysis through latent growth modeling, multilevel data analysis through multilevel SEM, and mixture modeling (Al-Sayed Amer, 2018, pp. 19–20).

3. Objectives of Structural Equation Modeling

The best model is the one that aligns with theory. Data, in turn, serve as a means to test that theory. Thus, structural equation modeling is a statistical approach designed to test theories or to examine the findings of previous studies.

The core idea behind structural equation modeling is to test a given theory by specifying a model that represents the expectations derived from that theory among a set of hypothetical constructs, which are measured through an appropriate set of observed variables. Failure of the model to fit the data is highly significant, as it represents a challenge to the theory. To achieve model fit, researchers may employ procedures such as model modification or the proposal of an alternative (competing) model.

Consequently, the primary objective of structural equation modeling (SEM) is to determine the degree of correspondence between the hypothesized model (constructed based on the study's hypotheses) and the collected data (Aishoush, 2015–2016, p. 143). In other words, it seeks to ascertain whether the hypothesized causal structure is consistent and compatible with the correlation or covariance matrix of the data under investigation (Becker, 1990, p. 25).

The main objectives of SEM can be summarized as follows:

- Testing or verifying complex, multidimensional, and interactive psychological phenomena within a single simultaneous analysis. This approach is particularly well-suited to the nature of human and social phenomena.
- Estimating model parameters, such as factor loadings of variables or items, direct and indirect effects, standard errors, and statistical significance, to evaluate the detailed components of the model.
- Estimating effect sizes to determine the proportion of variance explained in the endogenous (internal) latent dependent variable by the exogenous (external) latent variables. This allows for the assessment of effect size for each structural equation.
- Examining interaction effects among variables. Interaction effects are common in the human sciences, where the interaction between two variables may generate a third variable that influences the phenomenon. SEM methodology is capable of generating these interactions and investigating their effects on dependent variables (Al-Sayed Amer, 2018, p. 23).

4. Fundamental Principles of Structural Equation Modeling

Structural equation modeling, as a methodology, relies on several core concepts. It cannot be used effectively or with high precision unless these foundational principles are properly understood. These include the concept of the model itself, the nature of the variables that constitute the model, and the most commonly used types of models, such as path analysis models, structural models, and confirmatory factor analysis models.

4.1. The Concept of the Model

A model is generally defined as a representation or simulation of a phenomenon. Some scholars describe it as a symbolic, artificial expression or conceptualization of a situation or problem that facilitates clear understanding and serves as a basis for sound decision-making (Al-Sayed Amer, 2018, p. 15).

In this context, a model is a hypothesized pattern of direct and indirect linear relationships among a set of latent and observed variables (Robert & James, 2000, p. 202).

In the humanities and social sciences, a model is a description of a psychological, social, or psycho-social phenomenon in terms of multiple and often complex variables, reflecting the complexity of these phenomena that study human behavior—whether at the individual level or within groups and societies. These interrelated relationships among variables enable a deeper understanding of complex individual and collective human behavior.

4.2. The Nature of Variables in the Model

There are multiple classifications of variables in structural equation modeling. In this section, we focus on the three most important classifications:

4.2.1. First Classification: Latent and Observed Variables

- **a. Latent Variables** Latent variables reflect the underlying structure of the trait being measured. In statistical analysis, researchers often rely on the total scale score, and sometimes on the score of each dimension separately. However, when a researcher is able to combine all dimensions into a single hypothetical underlying component, this is referred to as a latent variable or factor.

For example, attitude consists of three dimensions: the affective, behavioral, and cognitive dimensions. The researcher treats these three dimensions as a single unified component (Al-Sayed Amer, 2018, p. 27). These three dimensions collectively form what is known as the latent variable. A latent variable is one that cannot be measured or observed directly but is inferred through a set of indicators, which may include questionnaire items, scales, tests, surveys, or other data collection instruments.

Latent variables are hypothetical or theoretical constructs (Constructs) that cannot be observed directly (Al-Mahdi, 2007, p. 11). They are also referred to as unmeasured variables, factors, unobserved variables, or hypothetical structures (Bollen, 2002, p. 607).

The first type is the latent variable—a variable that cannot be measured directly but is represented through the covariances among two or more indicator variables. Thus, a latent variable is essentially a label for a factor (in factor analysis) or a component (in principal component analysis). It is a structure that cannot be measured directly (e.g., depression), but can be accessed through the measurement of related variables (e.g., items on the Beck Depression Inventory).

- **b. Observed (Manifest) Variables** Observed or manifest variables are a set of variables used to identify or infer the underlying structure or latent variable (Hershberger et al., p. 4).

This applies to most variables that are measured directly and reflect the trait explicitly, such as intelligence or motivation. In these cases, the total score on an intelligence test or a motivation scale is called the measured score, regardless of whether the scale consists of a single dimension or multiple dimensions (Al-Sayed Amer, 2018, p. 26).

4.2.2. Second Classification: Exogenous and Endogenous Variables

- **a. Exogenous Variables** Exogenous variables are independent variables with no prior causal variable within the model. They exert influence but are not influenced; that is, they affect other variables but are not affected by any variable inside the model. Examples include measurement errors and any other independent variables within the model that influence but are not influenced.
- **b. Endogenous Variables** Endogenous variables are those that are affected by other variables within the model. They include both purely dependent variables and mediating variables. Mediating variables serve as outcomes of exogenous variables or

other mediating variables, and as causes for other dependent or mediating variables. In short, any variable toward which an arrow points in the model is considered endogenous (Al-Sayed Amer, 2018, p. 18).

4.2.3. Third Classification: Direct and Indirect Effects

- **a. Direct Effect Variables** These are variables that directly influence another variable within the model.
- **b. Indirect Effect Variables** These are variables that influence another variable through an intervening (mediating) variable within the model (Al-Mahdi, 2007, p. 13).

4.3. Types of Models

There are four main types of structural models: the regression analysis model, the path analysis model, the measurement model, and the full structural equation modeling model (structural model).

4.3.1. Regression Analysis Model

Regression models consist solely of observed variables. In these models, an observed dependent variable is explained or predicted by one or more observed independent variables (Al-Mahdi, 2007, p. 14).

For example, the leadership competency score of a company manager can be used to predict employees' job satisfaction. This is another illustrative example of regression analysis. Such models can be implemented using SPSS as well as specialized SEM software such as AMOS or SmartPLS.

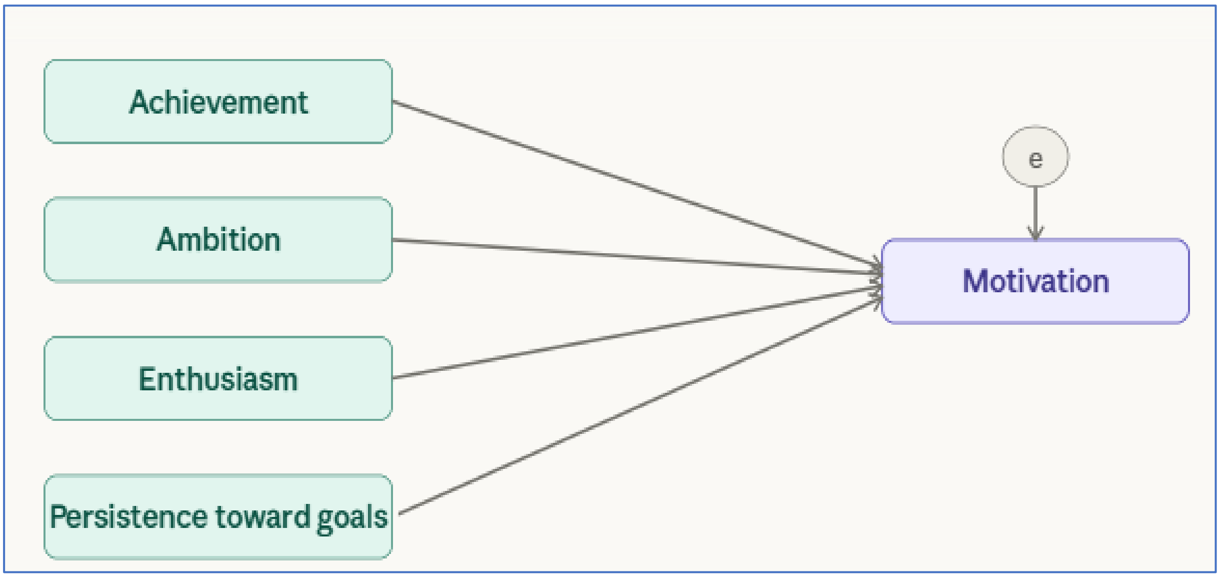

Figure (01) illustrates an example of a regression analysis model.

- This model includes only observed (measured) variables, with no latent variables present.
- The regression analysis model differs from the path analysis model in that it does not involve indirect relationships.
- The type of error in this model is referred to as "prediction error."

4.3.2. Path Analysis Model

Path analysis is a model that depicts both direct and indirect relationships among a set of observed variables. According to Al-Sayed Amer, the path analysis model aims to examine causal effects among measured variables (typically total scores). Some researchers do not consider it a type of SEM; however, it is in fact an important part of the historical development that led to the emergence of SEM. It employs the same underlying principles, assumptions, estimation procedures, and model fit criteria as SEM (Al-Sayed Amer, 2018, pp. 27–28).

Taghza adds that the path analysis model involves a network of unidirectional linear relationships indicating the effect of measured variables on other measured (observed) variables. Each effect relationship is represented by a single-headed arrow called a path .The fundamental difference between path analysis and regression analysis is that path analysis allows the researcher to explore reciprocal influence relationships among the variables under study, regardless of whether they are independent or dependent. In contrast, regression analysis only identifies the effect of independent variables on dependent variables and does not allow examination of how dependent variables influence one another. Consequently, path analysis models usually test more complex structures than regression models (Al-Mahdi, 2007, p. 15).

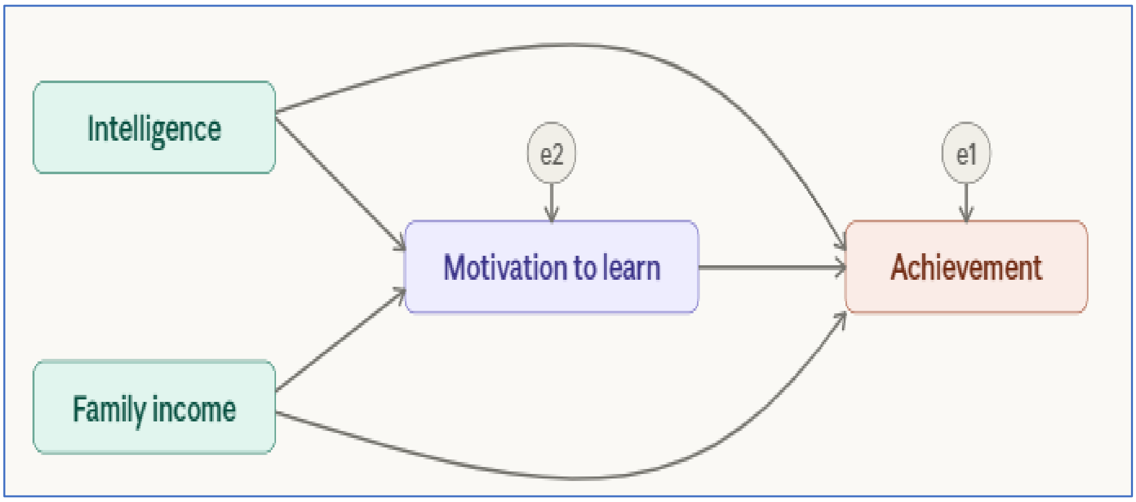

Figure (02) illustrates an example of a path analysis model.

From an analytical reading of the example in Figure (02), we observe that the variables enclosed in rectangles are observed or measured (manifest) variables. These are divided into two types: independent or exogenous variables and dependent or endogenous variables. In this example, there are two independent variables: intelligence and family income.

According to Taghza, independent variables are explanatory variables (the researcher assumes they account for the variance in the dependent variable they influence). They are also described as predictive or causal variables that exert an effect on the endogenous dependent variables. Their influence is represented by straight arrows originating from the independent (exogenous) variables and terminating at the dependent (endogenous) variables. These straight arrows are called paths (Taghza, 2011, p. 146).

A closer analytical examination of the variable "learning motivation" in Figure (02) reveals that the two arrows originating from the independent variables (intelligence and family income) terminate at it. This indicates that both variables influence learning motivation. At the same time, an arrow emanates from learning motivation and terminates at academic achievement. This means that learning motivation acts as a dependent (endogenous) variable with respect to intelligence and family income, while simultaneously functioning as an independent (exogenous) variable with respect to academic achievement. Consequently, it plays a dual role—both influencing and being influenced—and thus serves a mediating role in the relationship between the two independent variables (intelligence and family income) and the dependent variable (academic achievement).

This model expresses the following relationships:

- **Correlational relationships**: A correlation between intelligence and family income.
- **Direct relationships**: – The relationship between intelligence and academic achievement. – The relationship between family income and academic achievement.
- **Indirect relationships**: – The relationship between intelligence and academic achievement mediated by "learning motivation." – The relationship between family income and academic achievement mediated by "learning motivation."

The characteristics of the path analysis model can be summarized as follows:

- It includes only observed variables.
- It incorporates both direct and indirect relationships.
- The model includes another type of variable known as the "mediating variable."
- The mediating variable in this model may assume multiple roles, acting as both independent and dependent at the same time (e.g., learning motivation in the figure above).
- Path analysis assumes that the model is free from measurement errors, treating observed variables as fixed and free of random error. It also assumes the absence of specification errors.

4.3.3. Measurement Model

This model illustrates the relationship between latent variables and the indicators used to measure them, as is the case in confirmatory factor analysis (CFA).

The illustrative example provided is a model of the concept of creative thinking with its three dimensions (originality, flexibility, and fluency). This is essentially a factor-analytic model. Factor models are analytical in nature because they seek to decompose a specific concept or variable into its underlying dimensions or factors that form its structure or are hypothesized to constitute its structural framework.

In Figure (03), each latent factor is loaded by a set of indicators: the first latent factor (fluency) is loaded by six indicators (C1…C6), the second latent factor (flexibility) is also loaded by six indicators (C7…C12), and the third latent factor (originality) is loaded by six indicators (C13…C18). The model assumes that the three factors are correlated and not independent. There is also a residual portion called residuals (measurement errors), which represents the part of the variance that the latent factor cannot explain.

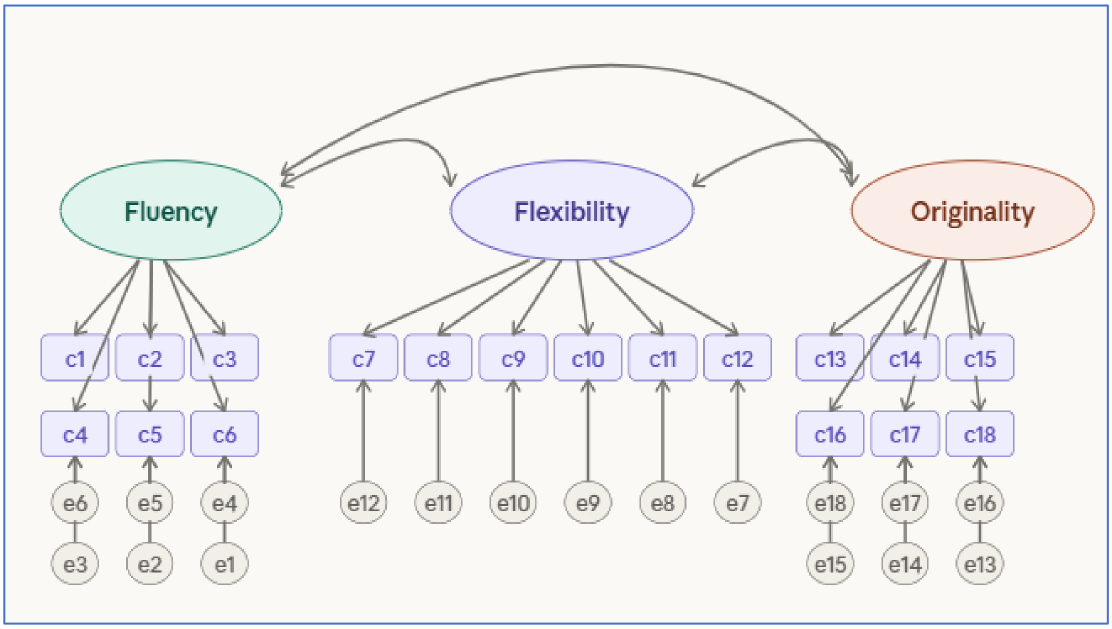

Figure (03) illustrates a Measurement model.

The characteristics of the measurement model can be summarized as follows:

- It includes latent variables (originality, flexibility, fluency) and observed variables (C1……C18).
- The errors in the measurement model are called "measurement errors" (e1……e18).

  Important Note: If a single-headed arrow connects latent variables, the model then becomes a "structural model," which will be discussed in the next section.

4.3.4. Structural Model

This model specifies the relationships among latent variables within the structural framework. It resembles confirmatory factor analysis but assumes the existence of causal effects between latent variables. It is used for several purposes, most notably testing explanatory (causal) relationships among a set of underlying structures (latent variables) or testing specific theories (Al-Sayed Amer, 2018, p. 29).

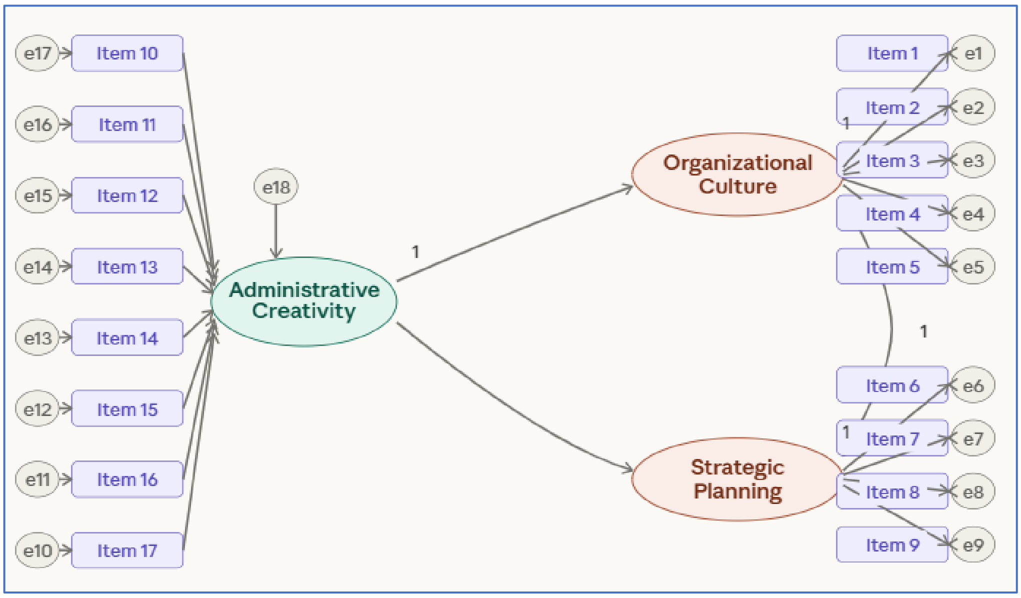

Figure (04) illustrates a structural model.

a. Characteristics of the Structural Model:

- The structural model is distinguished from the path analysis model by the presence of single-headed arrows connecting latent variables.
- The structural equation model consists of two main parts:

➢ **Measurement component**:
This includes a latent variable along with the measured indicators that assess it (see Figure 05).

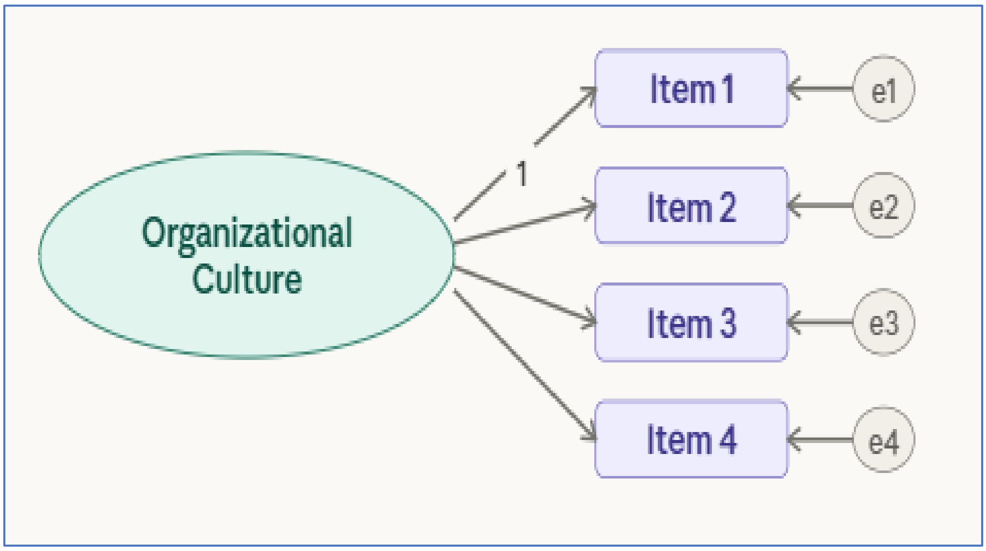

Figure (05) illustrates a Measurement component

➢ **Structural component:**
This includes the latent variables and the relationships among them (see Figure 06).

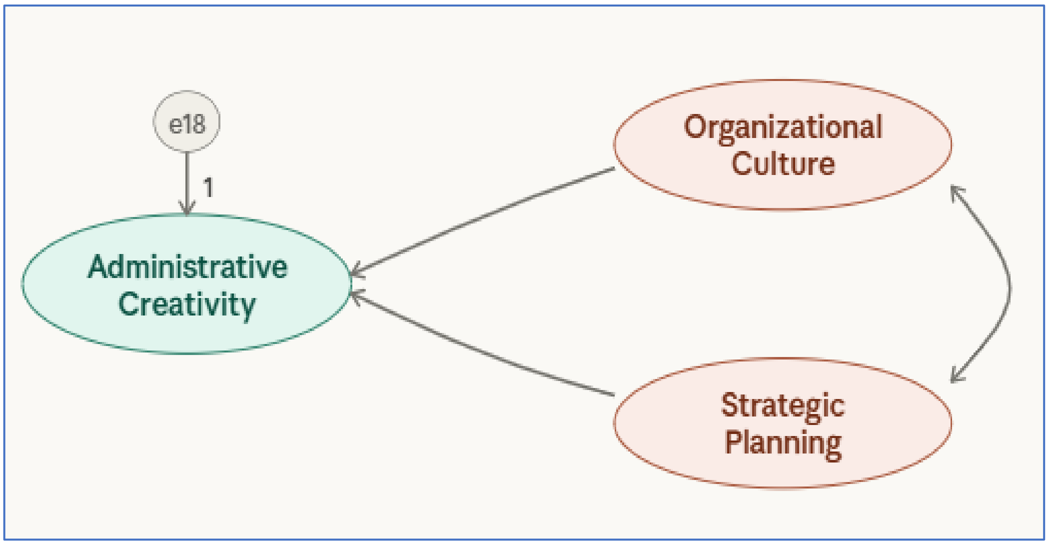

Figure (06) illustrates a Structural component

b. Components of the Structural Model:

There are two main components within the model: the measurement model and the structural model. The measurement model is the part of the overall model in which latent variables are described by specifying the measured variables (indicators) that serve as indicators of a latent variable (or factor). The structural model is the part in which relationships are specified between latent variables and other measured variables that are not indicators of any latent variables. These two components are combined to create a complete model that comprehensively describes the relationships among variables that are free from measurement error (i.e., the latent variables).

4.3.5. Confirmatory Factor Analysis Model

Confirmatory factor analysis aims to determine the nature of the internal correlational relationships among latent variables (factors) on the one hand, and between measured variables (items) and latent variables on the other. Each latent variable is defined by a set of measured variables (indicators). No causal effects are assumed between latent variables. It is primarily used to verify the validity of pre-specified measures in light of strong theoretical foundations (Al-Sayed Amer, 2018, p. 28).

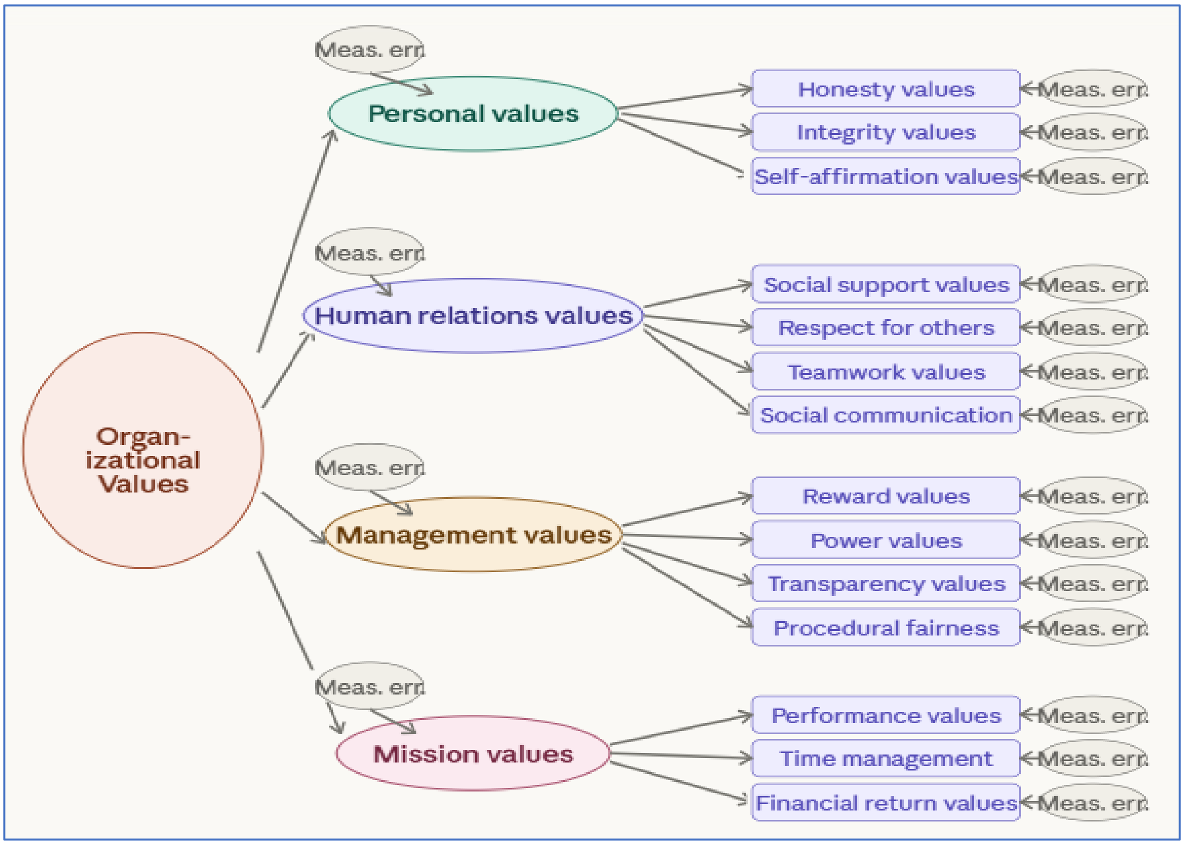

Figure (07) illustrates a second-order confirmatory factor model for the concept of organizational values.

4.3.6. Latent Change Model (LCM)

This is a methodology that provides a framework for studying changes in individuals or groups over time with respect to latent variables. It is used in longitudinal studies and is known by several names, including Latent Growth Modeling and Latent Curve Model (Al-Sayed Amer, 2018, p. 28).

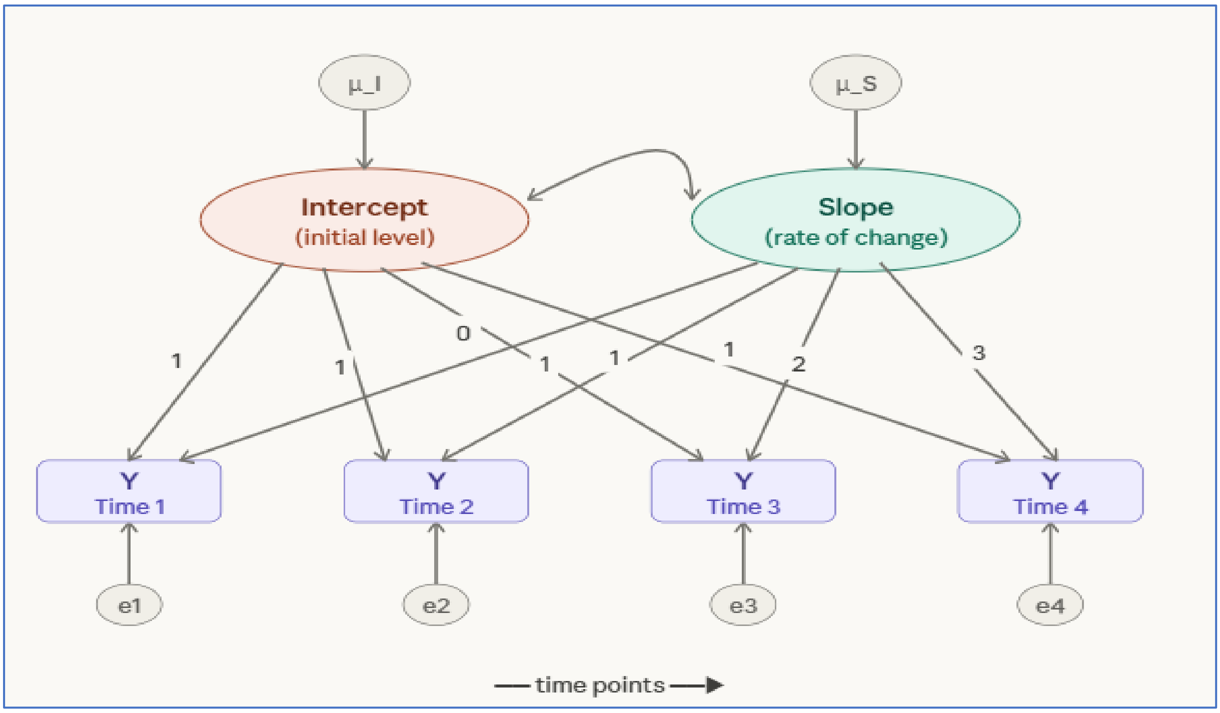

Figure (08) illustrates Latent Change Model (LCM)

Conclusion

Structural Equation Modeling represents a modern and advanced strategy in psychological, behavioral, human, and social sciences alike. It integrates several analytical strategies, including regression analysis, path analysis, exploratory factor analysis, and confirmatory factor analysis. It contributes significantly to validating previous theories in the humanities and social sciences in particular, given the exceptional complexity involved in studying human phenomena. It is also relied upon for verifying the validity of causal models among variables in general.

As a result, contemporary research trends have increasingly focused on adopting SEM as an innovative and comprehensive strategy for investigating complex human phenomena. Such phenomena require a holistic and interconnected analysis due to the multitude of overlapping, diverse, and interrelated variables involved.

References

Aishoush, R. (2016). *The role of strategic knowledge management in enhancing the competitive response of the economic institution: A study on a sample of electronic industry institutions in Bordj Bou Arreridj Province* [Doctoral dissertation, Mohamed Khider University of Biskra].

Al-Mahdy, Y. F. H. (2007). Structural Equation Modeling Method (SEM) and applications in educational administration researches. *Education and Development, 40*, 9–41. https://doi.org/10.13140/RG.2.2.18669.90089/1

Al-Qahwaji, A. S., & Abu Awwad, F. M. (2018). *Structural equation modeling using AMOS program: An applied study*. Dar Wael for Publishing and Distribution.

Amer, A. E. S. (2014). Evaluating the use of structural equation modeling applications in psychological research. *Arab Studies in Psychology (Ranem)*, *13*(4), 701–777. http://search.mandumah.com/Record/700164

Bollen, K. A. (2002). Latent variables in psychology and the social sciences. *Annual Review of Psychology, 53*(1), 605–634. https://doi.org/10.1146/annurev.psych.53.100901.135239

Byrne, B. M. (2001). *Structural equation modeling with AMOS: Basic concepts, applications, and programming* (3rd ed.). Routledge. https://doi.org/10.4324/9781315757421

Hershberger, S. L. (2003). The growth of structural equation modeling: 1994–2001. *Structural Equation Modeling, 10*(1), 35–46. https://doi.org/10.1207/S15328007SEM1001_2

Kline, R. B. (2016). *Principles and practice of structural equation modeling* (4th ed.). The Guilford Press.

Shaker, A. H. (2007). *Statistical analysis in psychological and educational research*. Dar Al-Fikr Al-Arabi.

Taghza, M. (2011). *Statistical analysis using structural equation modeling*. Diwan Al-Matbouat Al-Jami'iya.

Taghza, M. (2018). *Advanced statistical analysis using structural equation modeling*. Diwan Al-Matbouat Al-Jami'iya.