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Structural Equation Modelling (SEM) in Research: Narrative Literature Review

Rachmat Hidayat[1*], Patricia Wulandari[2]

[1]Department of Biology, Faculty of Medicine, Universitas Sriwijaya, Palembang, Indonesia

[2]Cattleya Mental Health Center, Palembang, Indonesia

*email: rachmathidayat@fk.unsri.ac.id

Abstract

The structural equation modeling (SEM) method has stronger predicting power than path analysis and multiple regression because SEM is able to analyze to the deepest level of the variables or constructs studied. This literature review aims to describe the use of structural equation modeling in research. In general, SEM can be used to analyze research models that have several independent (exogenous) and dependent (endogenous) variables as well as moderating or intervening variables. SEM provides several benefits and advantages for researchers, including building research models with many variables, researching variables or constructs that cannot be observed or cannot be measured directly (unobserved), testing measurement errors for observed variables or constructs and confirmatory factor analysis. The outline of the SEM method can be classified into two types, namely covariance based structural equation modeling (CB-SEM) and variance or component based SEM (VB-SEM) which includes partial least square (PLS) and generalized structural component analysis (GSCA). This literature review aims to describe the use of structural equation modeling in research.

Keywords: Data analysis, Predicting power, Social research, Structural equation modelling, Variable.

1.Introduction

Thebasic human beings want to continue to advance and develop in order to achieve a better quality of life. This is also the case in the world of research. Experts in the social or behavioral sciences including management consistently continue to develop research methods that

can be used to obtain better, perfect, fast, accurate, effective and efficient quality research results. Experts in the field of social or behavioral sciences including management have developed a research method called Structural Equation Modeling (SEM). At first, the SEM method was only good at the level of conception. The SEM method at that time still could not be operationalized due to technological limitations. With the rapid development of computer technology, the SEM method today is becoming increasingly known and widely used in behavioral and management research. The SEM method is a development of path analysis and multiple regression which are both forms of multivariate analysis models. In associative, multivariate-correlational or causal-effect analyses, the SEM method seems to break the dominance of the use of multiple path and regression analysis that has been used for decades. Compared to path analysis and multiple regression, the SEM method is superior because it can analyze data more comprehensively. Data analysis on path analysis and multiple regression is only carried out on variable total score data which is the sum of the items of the research instrument. Thus, path analysis and multiple regression are actually performed only at the level of latent (unobserved) variables. Meanwhile, data analysis on the SEM method can pierce deeper because it is carried out on each question item score of a research variable instrument. Instrument items in SEM analysis are referred to as manifest variables (observed) or indicators of a construct or latent variable.

The SEM method has stronger predicting power than path analysis and multiple regression because SEM is able to analyze to the deepest level of the variables or constructs studied. The SEM method is more comprehensive in explaining research phenomena. Meanwhile, path analysis and multiple regression are only able to reach the level of latent variables so that they experience a dead end to parse and analyze empirical phenomena that occur at the level of grains or indicator indicators of latent variables. Judging from the data used, path analysis and multiple regression actually only reach the outer shell of a research model. Meanwhile, the SEM method can be likened to being able to reach and parse and analyze the deepest entrails of a research model. The SEM method is expected to be able to answer the weaknesses and deadlocks faced by the previous generation of multivariate methods, namely path analysis and multiple regression. The development of SEM methods is becoming increasingly significant in the practice of social, behavioral and management research along with the advancement of information technology. Many multivariate statistical methods that in the 1950s were difficult to operationalize manually, such as factor analysis, multiple regression of more than three free variables, pathway analysis and

discriminant analysis gradually became inevitable due to the invention of computer programs such as: SPSS (Statistical Package for Social Science), Minitab, Prostate, QSB, SAZAM, etc. The SEM method is currently estimated to be the most dominant multivariate method. Computer programs that can currently be used to process data in SEM method research include AMOS, LISREL, PLS, GSCA, and TETRAD. This literature review aims to describe the use of structural equation modeling in research.

Benefits of SEM in penelitian

In general, SEM can be used to analyze research models that have several independent (exogenous) and dependent (endogenous) variables as well as moderating or intervening variables. SEM provides several benefits and advantages for researchers, including building research models with many variables, researching variables or constructs that cannot be observed or cannot be measured directly (unobserved), m testing measurement errors for observed variables or constructs, m confirming the theory in accordance with research data (confirmatory factor analysis), dapat answers various research problems in a set of analysis more systematically and comprehensively; lis illustrative, robust and reliable compared to regression models when modeling interaction, non-linearity, error measurement, error terms correlation, and correlation between multiple independent latent variables; duse as an alternative to path analysis and time series data analysis based on covariates; analysis of factors, pathways and regressions; explain the complex interrelationships of variables and the direct or indirect effects of one or more variables on another; and havegreater flexibility for researchers to link theory to data.

3. Types of SEM

As stated above, broadly speaking, the SEM method can be classified into two types, namely covariance based structural equation modeling (CB-SEM) and variance or component based SEM (VB-SEM) which includes partial least square (PLS) and generalized structural component analysis (GSCA). Variance is the deviation of the data from the mean (average) value of the sample data. Variance measures the deviation of data from the mean value of a sample, so it is a measure for metric variables. Mathematically, variance is the average of the squared differences between each observation and the mean, so variance is the mean value of the squared mean of the standard deviation. A variable must have a variance that is always positive, if it is zero

then it is not a variable but a constant. While covariance shows the linear relationship that occurs between two variables, namely X and Y. If a variable has a positive linear relationship, then the covariance is positive. If the relationship between X and Y is opposite, then the covariance is negative. If there is no relationship between the two variables X and Y, then the covariance is zero.

Covariance based structural equation modeling (CB-SEM)

Covariance-based SEM (CB-SEM) was first developed by Joreskog (1973), Keesling (1972) and Wiley (1973). CB-SEM became popular after the availability of the LISREL III program developed by Joreskog and Sorbom in the mid-1970s. By using the maximum likelihood (ML) function, CB-SEM seeks to minimize the difference between the sample covariance matrix and the predicted covariance matrix by theoretical models so that the estimation process produces a residual covariance matrix whose value is small near zero. Some things that need to be considered in the CB-SEM analysis include:

a. The assumption of using CB-SEM is like parametric analysis. The assumption that must be met is that the observed variables must have a multivariate normal distribution and the observations must be independent of each other. If the sample is small and not asymptomatic, it will give poor results of paramater estimates and statistical models or even produce a negative variant called the Heywood Case.

b. A small sample count will potentially result in a Type II error i.e. a bad model still produces a fit model.

c. CB-SEM analysis requires the form of latent variables whose indicators are reflective. In reflective models, indicators or manifests are considered variables that are influenced by latent variables according to the classical theory of measurement. In reflective indicator models, indicators on a construct (latent variable) are influenced by the same concept. Changes in one item or indicator will affect changes in other indicators in the same direction. The example referred to as a reflective variable is:
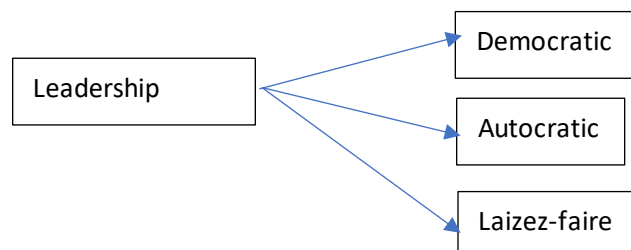
Figure 1. An example of a reflective variable of a latent variable (construct). Democratic, autocratic and Laizez-faire are the variables of the chorusofleadership. Reflective variables are variables that stay away from latent variables (constructs) as seen in the blue arrow above.

Variance based SEM (VB-SEM)

 PLS-SEM

PLS-SEM aims to test predictive relationships between constructs by seeing if there are relationships or influences between them. The logical consequence of the use of PLS-SEM is that testing can be carried out without a solid theoretical basis, ignoring some assumptions (non-parametric) and the parameters of the accuracy of the prediction model in view of the value of the coefficient of determination (R^2). PLS-SEM is very appropriate to be used in research aimed at developing theories. PLS-SEM was developed to address testing that cannot be done with CB-SEM. For example, in testing formative variables, as for examples of formative variables below:
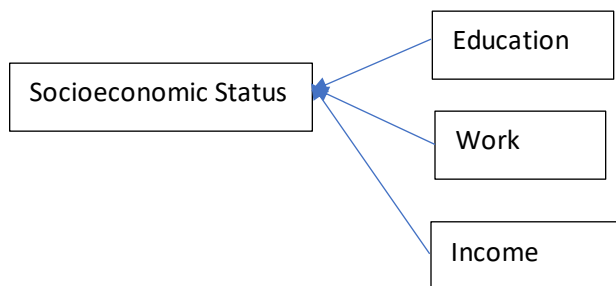

Figure 1. An example of a formative variable of a latent variable (construct). Education, Employment and Income are formative variables of socioeconomic status. Formative variables are variables that go to or affect or form latent variables (constructs) as seen in the blue arrow above.

GSCA

The GSCA combines the characteristics found in CB-SEM and PLS-SEM. The GSCA can handle latent variables with many indicators just like PLS-SEM, requiring the model's goodness of fit criteria and indicators and constructs to be correlated such as CB-SEM. The GSCA method to date has rarely been widely used by researchers because this method is relatively new. GSCA serves the same purpose as PLS-SEM, does not require the assumption of multivariate normality of data, and can be tested without a solid theoretical basis with a small number of samples.

Covariance-based SEM (CB-SEM) models are often called hard-modeling, while component-based or variance-based SEM (VB-SEM) modeling is called soft-modeling. Hard modeling aims to provide a statement of the causality relationship or provide a description of the mechanism of causality (cause-and-effect) relationships. This provides a scientifically ideal picture in data analysis. However, the data to be analyzed does not always meet the ideal criteria so it cannot be analyzed by hard modeling. As a solution, soft modeling tries to analyze data that is not ideal. Literally, soft actually means soft or soft, but in the context of soft research is defined as not basing on the assumption of measurement scale, data distribution and number of samples. The main objective of analysis with hard modeling is to test the causality relationships between those already built on the theory, whether the model can be confirmed with its empirical data. Meanwhile, the main purpose of soft modeling analysis is to find predictive linear relationships between latent constructs. It should be understood that causality or estimation relationships are not the same as predictive relationships. On causality relationships, CB-SEM looks for invariant parameters that structurally or functionally describe how systems in this world work. Invariant parameters describe causality relationships between variables in a closed system so that existing events can be fully controlled. Whereas in Partial Least Square, Variance or Component-Based SEM, the optimal linear relationship between latens is calculated and interpreted as the best predictive relationship available with all existing limitations. So that the existing events cannot be fully controlled. If the data to be analyzed meets all the assumptions required by CB-SEM, then researchers should analyze the data by hard modeling using appropriate software, such as AMOS, LISREL.

If the data does not meet all the required assumptions but the researcher continues to use hard modeling analysis or CB-SEM, then some of the problems that may be faced are: tbecome an im-proper solution or a solution that is not as effective, because of the Heywood Case, which is a symptom of a negative variant value; model becomes un-identified due to indeterminacy factors; and non-convergence algorithm. If the above conditions occur and we still want to analyze the data, then the goal we change is not to look for causality relationships between variables, but to find optimal predictive linear relationships using components or variance based-SEM.

Based on the objectives of empirical research, quantitative paradigms can be divided into two, namely estimates and predictions. Estimation research is research that aims to test an

empirical model with valid and reliable measurements. Tests and measurements are carried out at the indicator level. The hypothesis tested is the model hypothesis. The measurement criteria for testing the feasibility of a model are called goodness of fit tests. For estimation research purposes, CB-SEM is the right technique to use. Prediction research is research that aims to test the influence between constructs to predict causal relationships. Tests and measurements are carried out at the level of constructs or latent variables. The hypotheses carried out are generally partial hypotheses. Partial test criteria with predictive significance tests of relationships between variables using t-statistical tests. PLS-SEM and regression techniques are the right choice of statistical techniques to use. So component or variance based SEM (PLS and GSCA) is only used if the data we have cannot be solved with covariance based SEM (CB-SEM).

Conclusion

SEM can be used to analyze research models that have several independent and dependent variables as well as moderating or intervening variables.

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Submission acknowledgement

Dear author(s),

Rachmat Hidayat*, Patricia Wulandari has submitted the manuscript "Structural Equation Modelling (SEM) in Research: Narrative Literature Review" to Open Access Indonesia Journal of Social Sciences. The paper will be screened by editor and reviewed by peer review.

Cordially,

Prof. Paula Magnano, PhD
Editor

(*) Corresponding author

Bioscientia Medicina

Journal of Biomedicine and Translational Research

Peer Review Results

Dear author(s),

Rachmat Hidayat*, Patricia Wulandari has submitted the manuscript "Structural Equation Modelling (SEM) in Research: Narrative Literature Review" to Open Access Indonesia Journal of Social Sciences. The decision : Revision Required.

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Editor

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Reviewer 1: Revision required

<mark>**Structural Equation Modelling (SEM) in Research: Narrative Literature Review**</mark> →1

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<mark>**Abstract**</mark> →3

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1.Introduction →4

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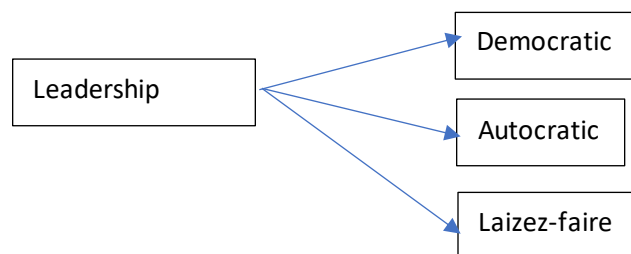
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```
┌─────────────────────────┐        ┌──────────────────┐
│                         │        │    Education     │
│  Socioeconomic Status   │◄───    └──────────────────┘
│                         │        ┌──────────────────┐
└─────────────────────────┘        │      Work        │
                                   └──────────────────┘
                                   ┌──────────────────┐
                                   │     Income       │
                                   └──────────────────┘
```
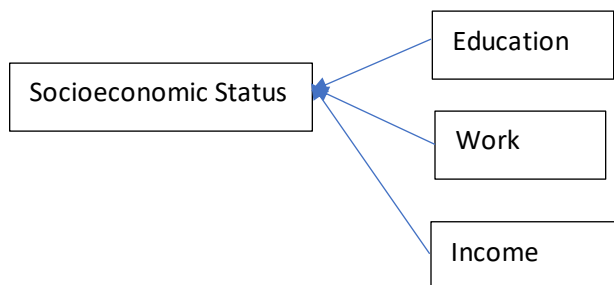
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The GSCA combines the characteristics found in CB-SEM and PLS-SEM. The GSCA can handle latent variables with many indicators just like PLS-SEM, requiring the model's goodness of fit criteria and indicators and constructs to be correlated such as CB-SEM. The GSCA method to date has rarely been widely used by researchers because this method is relatively new. GSCA serves the same purpose as PLS-SEM, does not require the assumption of multivariate normality of data, and can be tested without a solid theoretical basis with a small number of samples.

Covariance-based SEM (CB-SEM) models are often called hard-modeling, while component-based or variance-based SEM (VB-SEM) modeling is called soft-modeling. Hard modeling aims to provide a statement of the causality relationship or provide a description of the mechanism of causality (cause-and-effect) relationships. This provides a scientifically ideal picture in data analysis. However, the data to be analyzed does not always meet the ideal criteria so it cannot be analyzed by hard modeling. As a solution, soft modeling tries to analyze data that is not ideal. Literally, soft actually means soft or soft, but in the context of soft research is defined as not basing on the assumption of measurement scale, data distribution and number of samples. The main objective of analysis with hard modeling is to test the causality relationships between those already built on the theory, whether the model can be confirmed with its empirical data. Meanwhile, the main purpose of soft modeling analysis is to find predictive linear relationships between latent constructs. It should be understood that causality or estimation relationships are not the same as predictive relationships. On causality relationships, CB-SEM looks for invariant parameters that structurally or functionally describe how systems in this world work. Invariant parameters describe causality relationships between variables in a closed system so that existing events can be fully controlled. Whereas in Partial Least Square, Variance or Component-Based SEM, the optimal linear relationship between latens is calculated and interpreted as the best predictive relationship available with all existing limitations. So that the existing events cannot be fully controlled. If the data to be analyzed meets all the assumptions required by CB-SEM, then researchers should analyze the data by hard modeling using appropriate software, such as AMOS, LISREL.

If the data does not meet all the required assumptions but the researcher continues to use hard modeling analysis or CB-SEM, then some of the problems that may be faced are: tbecome an im-proper solution or a solution that is not as effective, because of the Heywood Case, which is a symptom of a negative variant value; model becomes un-identified due to indeterminacy factors; and non-convergence algorithm. If the above conditions occur and we still want to analyze the data, then the goal we change is not to look for causality relationships between variables, but to find optimal predictive linear relationships using components or variance based-SEM.

Based on the objectives of empirical research, quantitative paradigms can be divided into two, namely estimates and predictions. Estimation research is research that aims to test an empirical model with valid and reliable measurements. Tests and measurements are carried out at

the indicator level. The hypothesis tested is the model hypothesis. The measurement criteria for testing the feasibility of a model are called goodness of fit tests. For estimation research purposes, CB-SEM is the right technique to use. Prediction research is research that aims to test the influence between constructs to predict causal relationships. Tests and measurements are carried out at the level of constructs or latent variables. The hypotheses carried out are generally partial hypotheses. Partial test criteria with predictive significance tests of relationships between variables using t-statistical tests. PLS-SEM and regression techniques are the right choice of statistical techniques to use. So component or variance based SEM (PLS and GSCA) is only used if the data we have cannot be solved with covariance based SEM (CB-SEM).

Conclusion →5

SEM can be used to analyze research models that have several independent and dependent variables as well as moderating or intervening variables.

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1→ Title of Manuscripts should be explained main review and declared type of literature review: narrative or systematic review.

2→ Keywords should be showed the main words of the study, the authors can use MeSH to develop keywords.

3→ Abstract should be showed the main of background, main of review and conclusion of study.

4→Introduction should be showed the urgency of study (epidemiology data), biological plausibility concept, and lack of knowledge in the study.

5→ Conclusion should more specific and not more showed more review.

6→ Authors must check the references for make update references. References should no more than 10 years.

Reviewer 2: Revision required

Structural Equation Modelling (SEM) in Research: Narrative Literature Review →1

Rachmat Hidayat[1*], Patricia Wulandari[2]

[1]Department of Biology, Faculty of Medicine, Universitas Sriwijaya, Palembang, Indonesia

[2]Cattleya Mental Health Center, Palembang, Indonesia

*email: rachmathidayat@fk.unsri.ac.id

Abstract →3

The structural equation modeling (SEM) method has stronger predicting power than path analysis and multiple regression because SEM is able to analyze to the deepest level of the variables or constructs studied. This literature review aims to describe the use of structural equation modeling in research. In general, SEM can be used to analyze research models that have several independent (exogenous) and dependent (endogenous) variables as well as moderating or intervening variables. SEM provides several benefits and advantages for researchers, including building research models with many variables, researching variables or constructs that cannot be observed or cannot be measured directly (unobserved), testing measurement errors for observed variables or constructs and confirmatory factor analysis. The outline of the SEM method can be classified into two types, namely covariance based structural equation modeling (CB-SEM) and variance or component based SEM (VB-SEM) which includes partial least square (PLS) and generalized structural component analysis (GSCA). This literature review aims to describe the use of structural equation modeling in research.

Keywords: Data analysis, Predicting power, Social research, Structural equation modelling, Variable. →2

1.Introduction →4

Thebasic human beings want to continue to advance and develop in order to achieve a better quality of life. This is also the case in the world of research. Experts in the social or behavioral sciences including management consistently continue to develop research methods that can be used to obtain better, perfect, fast, accurate, effective and efficient quality research results.

Experts in the field of social or behavioral sciences including management have developed a research method called Structural Equation Modeling (SEM). At first, the SEM method was only good at the level of conception. The SEM method at that time still could not be operationalized due to technological limitations. With the rapid development of computer technology, the SEM method today is becoming increasingly known and widely used in behavioral and management research. The SEM method is a development of path analysis and multiple regression which are both forms of multivariate analysis models. In associative, multivariate-correlational or causal-effect analyses, the SEM method seems to break the dominance of the use of multiple path and regression analysis that has been used for decades. Compared to path analysis and multiple regression, the SEM method is superior because it can analyze data more comprehensively. Data analysis on path analysis and multiple regression is only carried out on variable total score data which is the sum of the items of the research instrument. Thus, path analysis and multiple regression are actually performed only at the level of latent (unobserved) variables. Meanwhile, data analysis on the SEM method can pierce deeper because it is carried out on each question item score of a research variable instrument. Instrument items in SEM analysis are referred to as manifest variables (observed) or indicators of a construct or latent variable.

The SEM method has stronger predicting power than path analysis and multiple regression because SEM is able to analyze to the deepest level of the variables or constructs studied. The SEM method is more comprehensive in explaining research phenomena. Meanwhile, path analysis and multiple regression are only able to reach the level of latent variables so that they experience a dead end to parse and analyze empirical phenomena that occur at the level of grains or indicator indicators of latent variables. Judging from the data used, path analysis and multiple regression actually only reach the outer shell of a research model. Meanwhile, the SEM method can be likened to being able to reach and parse and analyze the deepest entrails of a research model. The SEM method is expected to be able to answer the weaknesses and deadlocks faced by the previous generation of multivariate methods, namely path analysis and multiple regression. The development of SEM methods is becoming increasingly significant in the practice of social, behavioral and management research along with the advancement of information technology. Many multivariate statistical methods that in the 1950s were difficult to operationalize manually, such as factor analysis, multiple regression of more than three free variables, pathway analysis and discriminant analysis gradually became inevitable due to the invention of computer programs such

as: SPSS (Statistical Package for Social Science), Minitab, Prostate, QSB, SAZAM, etc. The SEM method is currently estimated to be the most dominant multivariate method. Computer programs that can currently be used to process data in SEM method research include AMOS, LISREL, PLS, GSCA, and TETRAD. This literature review aims to describe the use of structural equation modeling in research.

Benefits of SEM in penelitian

In general, SEM can be used to analyze research models that have several independent (exogenous) and dependent (endogenous) variables as well as moderating or intervening variables. SEM provides several benefits and advantages for researchers, including building research models with many variables, researching variables or constructs that cannot be observed or cannot be measured directly (unobserved), m testing measurement errors for observed variables or constructs, m confirming the theory in accordance with research data (confirmatory factor analysis), dapat answers various research problems in a set of analysis more systematically and comprehensively; lis illustrative, robust and reliable compared to regression models when modeling interaction, non-linearity, error measurement, error terms correlation, and correlation between multiple independent latent variables; duse as an alternative to path analysis and time series data analysis based on covariates; analysis of factors, pathways and regressions; explain the complex interrelationships of variables and the direct or indirect effects of one or more variables on another; and havegreater flexibility for researchers to link theory to data.

3. Types of SEM

As stated above, broadly speaking, the SEM method can be classified into two types, namely covariance based structural equation modeling (CB-SEM) and variance or component based SEM (VB-SEM) which includes partial least square (PLS) and generalized structural component analysis (GSCA). Variance is the deviation of the data from the mean (average) value of the sample data. Variance measures the deviation of data from the mean value of a sample, so it is a measure for metric variables. Mathematically, variance is the average of the squared differences between each observation and the mean, so variance is the mean value of the squared mean of the standard deviation. A variable must have a variance that is always positive, if it is zero then it is not a variable but a constant. While covariance shows the linear relationship that occurs

between two variables, namely X and Y. If a variable has a positive linear relationship, then the covariance is positive. If the relationship between X and Y is opposite, then the covariance is negative. If there is no relationship between the two variables X and Y, then the covariance is zero.

Covariance based structural equation modeling (CB-SEM)

Covariance-based SEM (CB-SEM) was first developed by Joreskog (1973), Keesling (1972) and Wiley (1973). CB-SEM became popular after the availability of the LISREL III program developed by Joreskog and Sorbom in the mid-1970s. By using the maximum likelihood (ML) function, CB-SEM seeks to minimize the difference between the sample covariance matrix and the predicted covariance matrix by theoretical models so that the estimation process produces a residual covariance matrix whose value is small near zero. Some things that need to be considered in the CB-SEM analysis include:

a. The assumption of using CB-SEM is like parametric analysis. The assumption that must be met is that the observed variables must have a multivariate normal distribution and the observations must be independent of each other. If the sample is small and not asymptomatic, it will give poor results of paramater estimates and statistical models or even produce a negative variant called the Heywood Case.

b. A small sample count will potentially result in a Type II error i.e. a bad model still produces a fit model.

c. CB-SEM analysis requires the form of latent variables whose indicators are reflective. In reflective models, indicators or manifests are considered variables that are influenced by latent variables according to the classical theory of measurement. In reflective indicator models, indicators on a construct (latent variable) are influenced by the same concept. Changes in one item or indicator will affect changes in other indicators in the same direction. The example referred to as a reflective variable is:
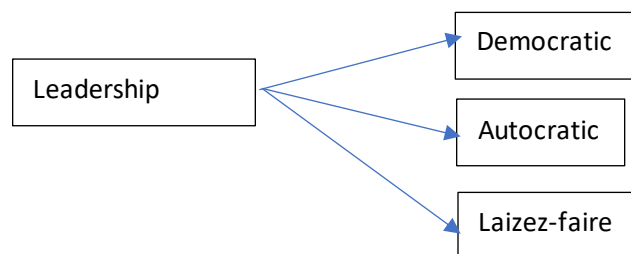
Variance based SEM (VB-SEM)

PLS-SEM

PLS-SEM aims to test predictive relationships between constructs by seeing if there are relationships or influences between them. The logical consequence of the use of PLS-SEM is that testing can be carried out without a solid theoretical basis, ignoring some assumptions (non-parametric) and the parameters of the accuracy of the prediction model in view of the value of the coefficient of determination (R^2). PLS-SEM is very appropriate to be used in research aimed at developing theories. PLS-SEM was developed to address testing that cannot be done with CB-SEM. For example, in testing formative variables, as for examples of formative variables below:
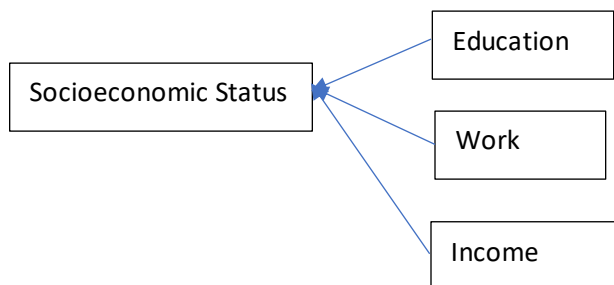

Figure 1. An example of a formative variable of a latent variable (construct). Education, Employment and Income are formative variables of socioeconomic status. Formative variables are variables that go to or affect or form latent variables (constructs) as seen in the blue arrow above.

GSCA

The GSCA combines the characteristics found in CB-SEM and PLS-SEM. The GSCA can handle latent variables with many indicators just like PLS-SEM, requiring the model's goodness of fit criteria and indicators and constructs to be correlated such as CB-SEM. The GSCA method to date has rarely been widely used by researchers because this method is relatively new. GSCA serves the same purpose as PLS-SEM, does not require the assumption of multivariate normality of data, and can be tested without a solid theoretical basis with a small number of samples.

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Murtaugh PA (2009) Performance of several variable-selection methods applied to real ecological data. Ecol Lett 12(10):1061–1068

Reviewer Comment:

1→ Title of Manuscripts should be explained main review and declared type of literature review: narrative or systematic review.

2→ Keywords should be showed the main words of the study, the authors can use MeSH to develop keywords.

3→ Abstract should be showed the main of background, main of review and conclusion of study.

4→Introduction should be showed the urgency of study (epidemiology data), biological plausibility concept, and lack of knowledge in the study.
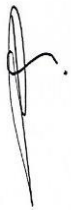
5→ Conclusion should more specific and not more showed more review.

6→ Authors must check the references for make update references. References should no more than 10 years.

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<u>Letter of Acceptance</u>

Manuscript "Structural Equation Modelling (SEM) in Research: Narrative Literature Review" by Rachmat Hidayat*, Patricia Wulandari, has been accepted to publish in Open Access Indonesia Journal of Social Sciences Vol 5 issue 6 in December 2022.

Cordially,

<u>Prof. Paula Magnano, PhD</u>
Editor

(*) Corresponding author
The Coresponding Author can access the acount in website :
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Structural Equation Modelling (SEM) in Research: Narrative Literature Review

Rachmat Hidayat[1*], Patricia Wulandari[2]

[1]Department of Biology, Faculty of Medicine, Universitas Sriwijaya, Palembang, Indonesia

[2]Cattleya Mental Health Center, Palembang, Indonesia

A B S T R A C T

The structural equation modelling (SEM) method has stronger predicting power than path analysis and multiple regression because SEM is able to analyze at the deepest level the variables or constructs studied. This literature review aimed to describe the use of structural equation modelling in research. In general, SEM can be used to analyze research models that have several independent (exogenous) and dependent (endogenous) variables, as well as moderating or intervening variables. SEM provides several benefits and advantages for researchers, including building research models with many variables, examining variables or constructs that cannot be observed or cannot be measured directly (unobserved), testing measurement errors (measurement errors) for observed variables or constructs (observed) and confirmatory factor analysis. Broadly speaking, SEM methods can be classified into two types, namely covariance-based structural equation modelling (CB-SEM) and variance or component-based SEM (VB-SEM), which includes partial least squares (PLS) and generalized structured component analysis (GSCA). This literature review aimed to describe the use of structural equation modelling in research.

1. Introduction

Human nature wants to continue to progress and develop in order to achieve a better quality of life. This also happens in the world of research. Experts in the social or behavioral sciences, including management, consistently develop research methods that can be used to obtain better, perfect, fast, accurate, effective, and efficient quality research results (Burhan, 2011). Experts in the field of social or behavioral sciences, including management, have developed a research method called structural equation modelling (SEM) (Byrne, 2013). At first, the SEM method was only good at the conception level. At that time, the SEM method could not be operationalized due to technological limitations. With the rapid development of computer technology, the SEM method is now becoming increasingly recognized and widely used in behavioral and management research (Capmourteres, 2016). The SEM method is a development of path analysis and multiple regression, which are both forms of multivariate analysis models. In an associative, multivariate-correlational, or causal-effect analysis, the SEM method seems to break the domination of the use of path analysis and multiple regression, which have been used for decades. Compared to path analysis and multiple regression, the SEM method is superior because it can analyze data more comprehensively (Chang, 1981). Data analysis in path analysis and multiple regression was only carried out on the total variable score data, which is the sum of

the research instrument items. Thus, path analysis and multiple regression are actually only carried out at the level of latent variables (unobserved). In comparison, data analysis in the SEM method can penetrate deeper because it is carried out on each item score of a research variable instrument. Instrument items in SEM analysis are referred to as manifest variables (observed) or indicators of a construct or latent variable (Chen, 2010).

The SEM method has stronger predicting power than path analysis and multiple regression because SEM is able to analyze at the deepest level the variables or constructs studied (Cohen, 2013). The SEM method is more comprehensive in explaining research phenomena. Meanwhile, path analysis and multiple regression are only able to reach the level of latent variables, so they experience a dead end in parsing and analyzing empirical phenomena that occur at the level of items or indicators of latent variables. Judging from the data used, path analysis and multiple regression actually only reach the outer shell of a research model (Cudeck, 1994). In comparison, the SEM method can be likened to being able to reach as well as parse and analyze the deepest entrails of a research model. The SEM method is expected to be able to answer the weaknesses and impasses faced by the previous generation of multivariate methods, namely path analysis and multiple regression (Curran, 2003). The development of SEM methods is becoming increasingly significant in the practice of social, behavioral, and management research, along with advances in information technology (Duncan et al., 2013). Many multivariate statistical methods which were difficult to operate manually in the 1950s, such as factor analysis, multiple regression with more than three independent variables, path analysis, and discriminant analysis, gradually became necessary because of the invention of computer programs such as SPSS (Statistical Package for Social Science), Minitab, Prostat, QSB, SAZAM, etc. The SEM method is currently estimated

to be the most dominant multivariate method. Computer programs that can currently be used to process data in SEM research methods include AMOS, LISREL, PLS, GSCA, and TETRAD. This literature review aims to describe the use of structural equation modeling in research (Eisenhauer et al., 2015).

The benefits of SEM in research

In general, SEM can be used to analyze research models that have several independents (exogenous) and dependent (endogenous) variables, as well as moderating or intervening variables (Fan et al., 1999). SEM provides several benefits and advantages for researchers, including building research models with many variables, examining variables or constructs that cannot be observed or cannot be measured directly (unobserved), testing measurement errors (measurement errors) for observed variables or constructs (observed), confirming the theory in accordance with research data (confirmatory factor analysis), being able to answer various research problems in a more systematic and comprehensive analysis set; more illustrative, robust and reliable than the regression model when modeling interaction, non-linearity, measurement error, correlation of error terms, and correlation between multiple independent latent variables; used as an alternative to path analysis and covariate-based time series data analysis; factor, path and regression analysis; explain the complex interrelationships of variables and direct or indirect effects of one or several variables on other variables; and has higher flexibility for researchers to relate the theory with data (Fritz et al., 2007; Grace, 2006).

Types of SEM

As stated above, in general, the SEM method can be classified into two types, namely covariance-based structural equation modelling (CB-SEM) and variance or component-based SEM (VB-SEM), which includes partial least squares (PLS) and generalized structured

component analysis (GSCA) (Grace, 2008; Grace, 2010). A variant is the deviation of the data from the mean (average) value of the sample data. Variance measures the deviation of data from the mean value of a sample, so it is a measure of metric variables. Mathematically, the variance is the average of the squared differences between each observation and the mean, so the variance is the average squared value of the standard deviation (Haavelmo, 1943). A variable must have a variance that is always positive. If it is zero, then it is not a variable but a constant. Meanwhile, covariance shows a linear relationship that occurs between two variables, namely X and Y. If a variable has a positive linear relationship, then the covariance is positive. If the relationship between X and Y is opposite, then the covariance is negative. If there is no relationship between the two variables, X and Y, then the covariance is zero.

Covariance-based structural equation modelling (CB-SEM)

Covariance-based SEM (CB-SEM) was first developed by Joreskog (1973), Keesling (1972), and Wiley (1973). CB-SEM became popular after the availability of the LISREL III program developed by Joreskog and Sorbom in the mid-1970s. By using the maximum likelihood (ML) function, CB-SEM tries to minimize the difference between the sample covariance matrix and the covariance matrix predicted by the theoretical model so that the estimation process produces a residual covariance matrix with a small value close to zero. Some things that need to be considered in CB-SEM analysis include the following: a) The assumption of using CB-SEM is like the parametric analysis. The assumptions that must be met are that the observed variables must have a multivariate normal distribution, and the observations must be independent of one another. If the sample is small and not asymptotic, it will give poor parameter estimates and statistical models or even produce a negative variance, which is called the Heywood Case. b) A small sample size will potentially result in a Type II error, i.e., a bad model will still result in a fit model. c) CB-SEM analysis requires the form of latent variables whose indicators are reflective. In the reflective model, indicators or manifest are considered variables that are influenced by latent variables according to the classical measurement theory. In the reflective indicator model, indicators in a construct (latent variable) are influenced by the same concept. Changes in one item or indicator will affect changes in other indicators in the same direction. The examples referred to as reflective variables are:
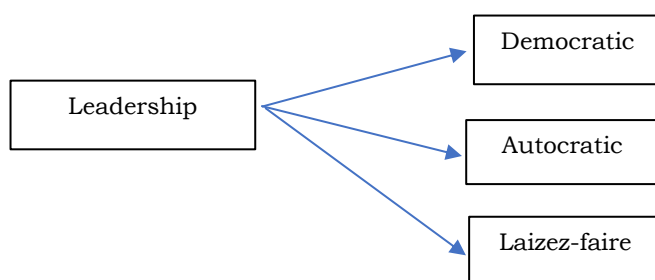

Figure 1. An example of a reflective variable from a latent (construct) variable. Democratic, autocratic, and Laizez-faire are reflective variables of leadership. Reflective variables are variables that stay away from latent (construct) variables, as shown in the blue arrows above.

Variance-based SEM (VB-SEM)
PLS-SEM

PLS-SEM aims to test predictive relationships between constructs by seeing whether there is a relationship or influence between these constructs (Hair et al., 2013). The logical consequence of using PLS-SEM is that testing can be carried out without a strong theoretical basis, ignoring some assumptions (non-parametric) and the parameter accuracy of the prediction model seen from the value of the coefficient of determination (R^2). PLS-SEM is very appropriate for use in research that aims to develop theory. PLS-SEM was developed to overcome tests that cannot be done with CB-SEM. (Harrington, (2009). For example, in testing formative variables, the examples of formative variables are as follows:
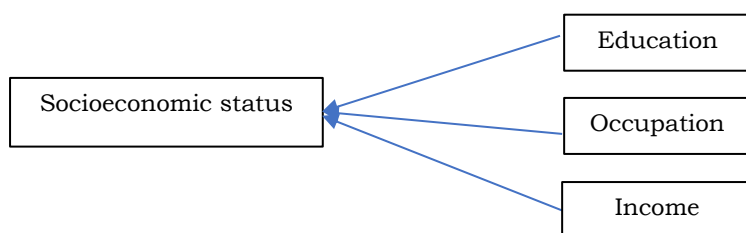

Figure 2. An example of a formative variable from latent (construct) variables. Education, Occupation, and Income are formative variables of socioeconomic status. Formative variables are variables that lead to or influence or form latent (construct) variables, as shown in the blue arrow above.

GSCA

GSCA combines the characteristics found in CB-SEM and PLS-SEM. GSCA can handle latent variables with many indicators, the same as PLS-SEM, requiring goodness of fit model criteria, and indicators and constructs must be correlated like CB-SEM. Until now, the GSCA method is rarely used widely by researchers because this method is relatively new. GSCA has the same goal as PLS-SEM, does not require the assumption of multivariate normality data, and can be tested without a strong theoretical basis with a small number of samples (Hoyle, 2013).

Model covariance-based SEM (CB-SEM) is often called hard modeling, while component-based or variance-based SEM (VB-SEM) modeling is called soft modeling. Hard modeling aims to provide a statement about the causality relationship or provide a description of the mechanism of the causality relationship (cause and effect). This provides an ideal picture scientifically in data analysis. However, the data to be analyzed does not always meet the ideal criteria, so it cannot be analyzed by hard modeling (Hu, 1999). As a solution, soft modeling tries to analyze data that is not ideal. Literally, soft actually means soft or soft, but in the research context, soft is defined as not based on assumptions on the scale of measurement, data distribution, and sample size (Iacobucci, 2010). The main purpose of analysis with hard modeling is to test the causal relationship between those that have been built based on the theory and whether the model can be confirmed with empirical data. In comparison, the main objective of soft modeling analysis aims to find predictive linear relationships between latent constructs. It should be understood that a causality or estimation relationship is not the same as a predictive relationship (Jackson et al., 2009). In terms of causality, CB-SEM looks for invariant parameters that structurally or functionally describe how the world's systems work. The invariant parameter describes the causal relationship between variables in a closed system so that events can be fully controlled. Whereas in Partial Least Square, Variance,

or Component-Based SEM, the optimal linear relationship between latents is calculated and interpreted as the best available predictive relationship with all the limitations that exist (Joreskog, 1993). So that the existing events can not be fully controlled, if the data to be analyzed meets all the assumptions required by CB-SEM, then the researcher should analyze the data by hard modelling using appropriate software, such as AMOS and LISREL (Kim, 2005).

If the data does not meet all the required assumptions, but the researcher still uses hard modelling or CB-SEM analysis, then several problems may be encountered, an improper solution or an imperfect solution because of the Heywood Case, which is a symptom of a negative variance value; the model becomes unidentified due to indeterminacy; and non-convergence algorithms. If that conditions occur and we still want to analyze the data, then our goal is not to change causality between variables but to find optimal predictive linear relationships using component or variance-based SEM (Lamb et al., 2014).

Based on the objective of empirical research, the quantitative paradigm can be divided into two, namely estimation and prediction. Estimation research is research that aims to test an empirical model with valid and reliable measurements. Testing and measurement are carried out at the indicator level. The hypothesis being tested is the model hypothesis. The measurement criterion for testing the feasibility of the model is called the goodness of fit test (LeCun et al., 2015). For estimation research purposes, CB-SEM is an appropriate technique to use. Prediction research is research that aims to examine the influence between constructs to predict causal relationships. Testing and measurement are carried out at the level of constructs or latent variables (McDonald, 2002). The hypothesis that is done is generally a partial hypothesis. Partial testing criteria with a significance test predicting the relationship between variables using the t-statistic test. PLS-SEM and regression techniques are the right

choices of statistical techniques to use (Mulaik et al., 1989; Murtaugh, 2009). Therefore, component or variance-based SEM (PLS and GSCA) is only used if the data we have cannot be solved with covariance-based SEM (CB-SEM).

2. Conclusion

SEM can be used to analyze research models that have several independent and dependent variables as well as moderating or intervening variables.

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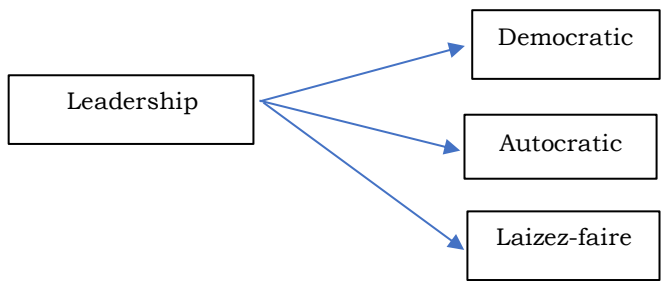

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PLS-SEM

PLS-SEM aims to test predictive relationships between constructs by seeing whether there is a relationship or influence between these constructs (Hair et al., 2013). The logical consequence of using PLS-SEM is that testing can be carried out without a strong theoretical basis, ignoring some assumptions (non-parametric) and the parameter accuracy of the prediction model seen from the value of the coefficient of determination (R^2). PLS-SEM is very appropriate for use in research that aims to develop theory. PLS-SEM was developed to overcome tests that cannot be done with CB-SEM. (Harrington, (2009). For example, in testing formative variables, the examples of formative variables are as follows:
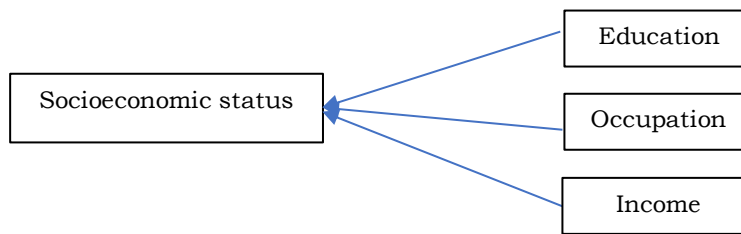

Figure 2. An example of a formative variable from latent (construct) variables. Education, Occupation, and Income are formative variables of socioeconomic status. Formative variables are variables that lead to or influence or form latent (construct) variables, as shown in the blue arrow above.

GSCA

GSCA combines the characteristics found in CB-SEM and PLS-SEM. GSCA can handle latent variables with many indicators, the same as PLS-SEM, requiring goodness of fit model criteria, and indicators and constructs must be correlated like CB-SEM. Until now, the GSCA method is rarely used widely by researchers because this method is relatively new. GSCA has the same goal as PLS-SEM, does not require the assumption of multivariate normality data, and can be tested without a strong theoretical basis with a small number of samples (Hoyle, 2013).

Model covariance-based SEM (CB-SEM) is often called hard modeling, while component-based or variance-based SEM (VB-SEM) modeling is called soft modeling. Hard modeling aims to provide a statement about the causality relationship or provide a description of the mechanism of the causality relationship (cause and effect). This provides an ideal picture scientifically in data analysis. However, the data to be analyzed does not always meet the ideal criteria, so it cannot be analyzed by hard modeling (Hu, 1999). As a solution, soft modeling tries to analyze data that is not ideal. Literally, soft actually means soft or soft, but in the research context, soft is defined as not based on assumptions on the scale of measurement, data distribution, and sample size (Iacobucci, 2010). The main purpose of analysis with hard modeling is to test the causal relationship between those that have been built based on the theory and whether the model can be confirmed with empirical data. In comparison, the main objective of soft modeling analysis aims to find predictive linear relationships between latent constructs. It should be understood that a causality or estimation relationship is not the same as a predictive relationship (Jackson et al., 2009). In terms of causality, CB-SEM looks for invariant parameters that structurally or functionally describe how the world's systems work. The invariant parameter describes the causal relationship between variables in a closed system so that events can be fully controlled. Whereas in Partial Least Square, Variance,

or Component-Based SEM, the optimal linear relationship between latents is calculated and interpreted as the best available predictive relationship with all the limitations that exist (Joreskog, 1993). So that the existing events can not be fully controlled, if the data to be analyzed meets all the assumptions required by CB-SEM, then the researcher should analyze the data by hard modelling using appropriate software, such as AMOS and LISREL (Kim, 2005).

If the data does not meet all the required assumptions, but the researcher still uses hard modelling or CB-SEM analysis, then several problems may be encountered, an improper solution or an imperfect solution because of the Heywood Case, which is a symptom of a negative variance value; the model becomes unidentified due to indeterminacy; and non-convergence algorithms. If that conditions occur and we still want to analyze the data, then our goal is not to change causality between variables but to find optimal predictive linear relationships using component or variance-based SEM (Lamb et al., 2014).

Based on the objective of empirical research, the quantitative paradigm can be divided into two, namely estimation and prediction. Estimation research is research that aims to test an empirical model with valid and reliable measurements. Testing and measurement are carried out at the indicator level. The hypothesis being tested is the model hypothesis. The measurement criterion for testing the feasibility of the model is called the goodness of fit test (LeCun et al., 2015). For estimation research purposes, CB-SEM is an appropriate technique to use. Prediction research is research that aims to examine the influence between constructs to predict causal relationships. Testing and measurement are carried out at the level of constructs or latent variables (McDonald, 2002). The hypothesis that is done is generally a partial hypothesis. Partial testing criteria with a significance test predicting the relationship between variables using the t-statistic test. PLS-SEM and regression techniques are the right

choices of statistical techniques to use (Mulaik et al., 1989; Murtaugh, 2009). Therefore, component or variance-based SEM (PLS and GSCA) is only used if the data we have cannot be solved with covariance-based SEM (CB-SEM).

2. Conclusion

SEM can be used to analyze research models that have several independent and dependent variables as well as moderating or intervening variables.

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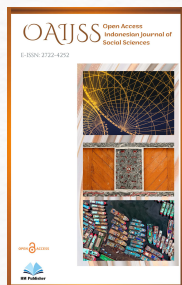## OF PUBLICATION

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