STRUCTURAL EQUATION MODELLING (SEM): OVERVIEW, APPLICATIONS, AND MISAPPLICATION IN SCIENCE AND TECHNOLOGY EDUCATION

Sunday Ogbu
sunday.ogbu@unn.edu.ng
Department of Science Education, Faculty of Education,
University of Nigeria, Nsukka

Abstract

Structural Equation Modelling (SEM) has become an increasingly important multivariate statistical technique in educational and social science research due to its ability to model complex relationships among observed and latent variables simultaneously. Traditional techniques such as multiple regression analysis and analysis of variance (ANOVA) are limited to directly measured variables and are less effective in handling measurement error, indirect effects, and complex model structures. This paper provides a comprehensive overview of SEM with special emphases on its conceptual foundations, common terminologies, types, and implementation procedures. Special attention was also given to the distinction between covariance-based SEM (CB-SEM) and variance-based SEM, also known as partial least squares SEM (PLS-SEM), including their underlying assumptions, objectives, and appropriate conditions for use. The paper further outlines the major steps involved in SEM implementation which include model specification, measurement model evaluation, and structural model assessment within the PLS-SEM framework. Most importantly, frequent misapplications of SEM in educational researches were highlighted. This paper aims to guide researchers toward more rigorous, theoretically grounded, and meaningful applications of SEM in educational research.

Introduction

The relationship between two variables can be examined using simple regression analysis. The relationship is always in such a way that one variable is a predictor and the other variable a criterion or outcome. These variables must be measured or observed variables. In a situation where there are more than two variables and one is interested in ascertaining how the variables are related, the multiple regression (MR) analysis or Analysis of variance ANOVA become the appropriate statistical tools. In ANOVA, the independent variables are categorical variables while the dependent variables are always controlling variable. ANOVA becomes less efficient when there are more categories of the independent variable. Although multiple regression analysis accommodates a greater number of both dependent and independent variables and examine the relationship among the variables, the variables needed in MR and ANOVA are measured or observed variables. In other words, MR and ANOVA are less effective in determining relationship among variables that are not measured directly or where summated scores are not used. The shortcomings of both MR and ANOVA pave way for Structural Equation Modelling (SEM), a more sophisticated and flexible statistical tool that could handle both latent and observed variables.

Structural equation modelling is a generic term for a family of related procedures and does not designate a single statistical tool (Kline, 2016). It is a family of statistical methods for modelling the relations between/among variables (Hoyle, 2012). It is a collection of statistical techniques that allow a set of relationship between one or more (continuous or discrete) independent variable(s) and one or more continuous or discrete dependent variable(s) to be determined (Ogbu et al., 2023). SEM is a comprehensive and flexible procedure that consists of studying, in a hypothetical model, the relationships between variable irrespective of how the variable are measured (Gana & Broc, 2019).

Because SEM is an umbrella term for set of statistical techniques for modelling relationship among variables that could be latent or observed, there are many terms being used interchangeable with SEM. Structural Equation modelling is also referred to as causal modelling, causal analysis, simultaneous equation modelling, analysis of covariance structure, path analysis or confirmatory factor analysis (Ullman, 2007). These terms arise because of the nature of SEM data and the intents for SEM studies. When the variable in SEM are latent variables, SEM could be rightly referred to as latent variable analysis. On the other hand, if the variables are measured or manifest variables, the term path analysis is often used in the place of SEM. If the intent of the study is to investigate causal relationships, the term causal modelling or causal analysis suffices. And because variance and covariance matrix are the main data structure in some type of SEM, people refer to

EM as analysis of covariance structure.

Regardless of the term being used, SEM is a combination of multiple regression analysis and Conformation Factor Analysis (CFA) that allows for comprehensive and flexibility in determining the relationship among variables. The CFA component of SEM allows for the relationship between latent variables and their indicators to be examined. On the other hand, regression analysis component allows the relationship among observed variables or latent variables to be examined. Providing a frame for examining these relations makes SEM a comprehensive statistical tool. In addition, the direct and indirect relationships that could be examined in SEM makes it more flexible as compared to other multivariate statistical tools.

Covariance-Based SEM and Variance-Based SEM

SEM could be conducted using covariance-based structural equation modelling (CB-SEM) or variance-based SEM (VB-SEM) also known as the partial least squares structural equation modelling (PLS-SEM).

CB-SEM vs. PLS-SEM: The CB-SEM estimates model parameters so that the discrepancy between the model implied and sampled covariance matrices is minimized. In the PLS-SEM, the explained variance of latent variable is maximised by estimating the partial model relationship in an iterative sequence of ordinary least squares regression (Monecke & Leisch, 2012). CB-SEM is used when the intent of the study is to confirm a theory. It is expected that before CB-SEM is used, that the data should be normally distributed and sample should be large enough. For the conditions to use PLS-SEM, (Risher et al., 2018, p. 5) advised that researchers should select PLS-SEM:

1. "when the analysis is concerned with testing a theoretical framework from a prediction perspective;
2. when the structural model is complex and includes many constructs, indicators and/ or model relationships;
3. when the research objective is to better understand increasing complexity by exploring theoretical extensions of established theories (exploratory research for theory development);
4. when the path model includes one or more formatively measured constructs;
5. when the research consists of financial ratios or similar types of data artefacts;
6. when the research is based on secondary/archival data, which may lack a comprehensive substantiation on the grounds of measurement theory;

7. when a small population restricts the sample size (e.g. business-to-business research); but PLS-SEM also works very well with large sample sizes;
8. when distribution issues are a concern, such as lack of normality; and when research requires latent variable scores for follow-up analyses".

Implementation of SEM

Every SEM study is implemented using a general framework. The general framework stipulates the steps that guide SEM. The steps are presented sequentially as follows: (i) specification, (ii) estimation, (iii) evaluation of fit and; (iv) interpretation and reporting. In addition to the 4 major steps, some authors have added a 5^{th} step; re-specification of model (Hoyle, 2012).

Common Terms Associated with SEM:

It is important that users of SEM are familiar with basic terms and symbols that generally associate with SEM and SEM studies. Some of these terms, although have been used in preceding sections, in this section, most of these terms are discussed as follows:

- **Measured variable (MV):** measured variable is a variable that is that has a single indicator. Measured variables can also be referred to as observed variable. The observed variable in SEM can be continuous, discrete or categorical variable. in SEM observed variable are often represented with rectangles or squares
- **Latent variables (LV):** latent variables are variables that are not measured directly. They are measured by observed variable. It is represented by a set of indicators. Latent variable refers to something that is in common among multiple indicators. Latent variables are represented, in strict sense, by individual items that reflected the construct and not by summated scores from the individual items. Considering LV as variables that are not measured directly, error term which are not measured directly are also regarded as latent variable. One should note that there is no absolute observed or latent variables. One variable may be used as latent variable in one study, and in another study, as observed variable. Latent variables can be converted to observed variable by either summing the indicators' scores and using the total score or the use of average to represent a respondent's score on the variable. Latent variables are represented by circles or oval shapes in structural model.
- **Model:** a model is a statistical statement about the relationship among the variables under consideration. It is a function that shows how changes in

variables interact. Within a given model, there is always at least one exogenous variable.

- **Exogenous variables:** exogenous variables are variable on the model that influence, affect or act on another variable. Exogenous variable can also be referred to as independent variable, predictor variable or input variable. Apart from exogenous variables in a model, there should also be at least on endogenous variable in a given structural model.
- **Endogenous variables:** endogenous variables receive the effect of the exogenous variable. Endogenous variable could also be referred to as dependent variable, criterion out outcome/output variable. In graphical representation of SEM, directional arrows point at the endogenous variables while directional errors start/originate from the exogenous variable. Note that a variable could be both exogenous and endogenous in a particular model. This is possible if it receives the effects of another exogenous variable and also influence another endogenous variable.
- **Effect size:** effect size is the measure of the strength of relationship between exogenous variable and endogenous variable (Coolidge, 2006). It can also be seen as the measure of the strength of treatment in an experimental study.
- **Path diagram:** path diagram can also be called path model. It is the diagrams that visually display the null hypotheses and variable relationships that are examined when structural equation modeling is applied. A path diagram is a pictorial or graphical representative of a model. In path diagram one could see the relationship among variable. The common three relations are association, direct effect and indirect effect. The association could be correlation between two variables often represented with curved double error.
- **Path coefficients:** path coefficients measures degree of relations among the hypothesised paths.
- **Reflective measurement model:** reflective measurement model is a type of measurement model setup in which the direction of the arrows is from the construct to the indicator variables, indicating the assumption that the construct causes the measurement (more precisely, the covariation) of the indicator variables.
- **Recursive model:** recursive model is a SEM path model that does not have a causal loop of relationships between latent variables in the structural model (i.e., no circular relationships).
- **Outer model:** outer model is referred to the relationship between an

indicator or a set of indicators and the latent variables measured by the indicators. The outer model is also called measurement model.

- **Inner model:** inner model is referred to the relationship between the latent variables. It can also be called structural model.
- **Bootstrap:** Bootstrap refers to generation of a certain number of sample randomly with replacement from the initial sample considered as the population. Each generated sample contains the same numbers of observation, as many estimates of the model parameters as there are generated samples will be calculated.
- **Indicator loading:** indicator loading is the bivariate correlation between indicator and the construct the indicator measures.
- **Internal consistency reliability:** internal consistency reliability is the extent the indicators of a given construct are related with each other.
- **Convergent validity:** convergent validity refers to the extent which the construct converges in other to explain the variance of its indicators (Hair, Hult, Ringle, Sarstedt, Dank, & Ray, 2022).
- **Average variance extracted (AVE):** AVE is the grand mean of the squared loadings of the indicators of a given construct.
- **Construct communality:** construct communality is equivalent to the average variance extracted (AVE).
- **Discriminant validity:** discriminant validity is the measure of the extent to which a construct is empirically difference from other construct in the hypothesized model.
- **Hetero-trait-mono-trait ratio (HTMT) of correlation:** HTMT is the mean value of the indicator correlation across construct related to the (geometric) mean of the average correlation for indicators measuring the same construct (Hair et al., 2022).
- **Indicator collinearity:** indicator collinearity is a situation where two or more indicators a formative model are highly correlated.
- **Confidence interval:** confidence interval is an alternative way for testing for significance in PLS-SEM.

Types of SEM:

Generally, there are basic types of structural equation models. These models are explained below:

1. Path Analysis Models: Path analysis models are SEM established with only observed variables. The basic of SEM depends on path analysis which was first developed Sewall Wright (Civelek, 2018). Path analysis depicts the relationship

among observed variables. In symbol notations, the variables in path analysis are all represented with squares or rectangles. There is close relationship between multiple regression and path analysis. Both make use of observed variables. However, path analysis could be considered as an extension of multiple regression. In multiple regression no dependent variable can served as a predictor variable. In path analysis there could be as man dependent variable as possible and these dependent variable could influence one another. More so, direct and indirect effects of independent variable on dependent variable can be examined simultaneously in path analysis which is not possible in multiple regression.

2. Confirmatory Factor Analysis: Confirmatory factor analysis (CFA) is one of the two types of factor analysis. The second is exploratory factor analysis (EFA). In EFA, there is no predetermined direction of factor loadings. Observed variable can be loaded in any factor. On the other hand, CFA, the observed variable that would be loaded in a given factor(s) are predetermined (mainly by theory). The purpose of CFA is to confirm predetermined specified model based on collected data.
3. Structural Regression Models: Structural regression models are regression models formed between latent variables in structural equation models (Civelek, 2018). It is coexistence of CFA and multiple regressions. Structural regression models could be regarded as the general form of SEM. Therefore, with adequate data, path analysis models could be converted to structural regression models whereby the observed variables in path models would be measured by certain indicators.
4. Latent Change Models: The latent change model could also call latent growth curve model latent grown analysis. The models explain the longitudinal variation in time series of a given variable See Kline (2016) for detail discussion of latent change models. Having been familiarized with the terms that are associated with SEM and types of SEM, one could be in best position to explore the necessary steps in SEM studies. The first step in SEM studies is specification.

Major Steps in Implementation of VB-SEM Studies

Specification

Specification is the expression of the researcher's hypothesized relations about variables of interest. To specify a model means to transcribes it for a given software for analysis, by using a syntax where operators are symbols (Gana&Broc 2019). Model specification is the formulation of a statement about a set of parameters that make up the model. Specification is the most important step in the structural equation modelling (Kline, 2016), because the results of later steps are hinged on whether the model is specified correctly or not. It has been noted that the initial decision in specification a model concerns the format that will be used to convey the specified model (Hoyle, 2012). The format is used to communicate the specified model to computer or to readers. In a broad sense, there are three formats of communicating a model to either SEM softwares or readers of SEM articles. These formats are (i) the use of graphical representation, (ii) the use set of equation and; (iii) the use of matrices algebra.

Evaluation of reflective Measurement Model Fit in PLS-SEM

Basically, the three aspects of reflective model that should be evaluated include: (i) unidimensionality of the indicators, (ii) checking that the indicators are well explained by its latent variable (iii) assess the degree to which a given construct is different from other constructs (Sanchez & Trinchera, 2013). The three basic aspects of reflective model can be summarized by the following steps outlined by Hair, Hult, Ringle, &Sarstedt (2018):

- ✓ The first step involves evaluating the indicator loadings. Loadings above 0.708 are considered acceptable and implies that the construct explains more than 50 percent of the indicators variance which means acceptable item reliability.
- ✓ The second step involves examining consistency reliability (composite reliability) using Dillon-Goldstein's rho and Cronbach's alpha. Reliability values between 0.60 and 0.70 are considered “acceptable”, values between 0.70 and 0.90 ranges from “satisfactory to good”, values of 0.95 and higher are problematic. It has been noted that values greater than or equal to 0.4 is an indication of acceptable good fit (Adewale, Metibemu, Anynwale, &Antia, 2020).
- ✓ The third step involves assessing the convergent validity of each construct. convergent validity entails the degree to which the construct converges to explain the variance of its items. The construct validity is measured by average variance extracted (AVE) for all the items. An acceptable AVE is 0.50 or higher which indicate that the construct explains at least 50% of the variance of its items.
- ✓ The next step involves assessing the discriminant validity which is the measure of the extent the construct is empirically distinct from other construct in the model. The best metric for discriminant validity is the heterotrait-monotrait (HTMT) ratio of correlation (Voorhees, Brady, Calantone, & Ramirez, 2016). The acceptable values of HTMT should be ≤ 0.90

***Evaluation of the Structural Model*:**

1. **Collinearity Assessment**
   Before interpreting results, you must ensure that predictor constructs are not highly correlated. This is measured via the Variance Inflation Factor (VIF): VIF < 3: Ideal; no collinearity issues. VIF 3–5: Generally acceptable/uncritical. VIF $\geq$ 5: Indicates potential critical collinearity problems.

2. **Path Coefficients and Effect Size**
   Use bootstrapping to determine if relationships are statistically significant based on t-values or confidence intervals. The size of the coefficient is evaluated using the effect size. Effect Size f^2: Assess the contribution of each exogenous construct. Thresholds for f^2 are: 0.02: Small, 0.15: Medium, and 0.35: Large.
3. **Explanatory Power (R^2 & GoF)**
   The Coefficient of Determination (R^2) measures how much variance is explained. Benchmarks: 0.75 (substantial), 0.50 (moderate), and 0.25 (weak). It needs to be noted that excessively high R^2 values may suggest over-fitting. Alternatively, use GoF where values GoF=0.1 are small, GoF=0.25 are medium, and GoF=0.36 are large (Knock, 2020).
4. **Predictive Power (PLSpredict)**
   Assess out-of-sample predictive relevance by focusing on a primary target construct. Use a 10-fold cross-validation (k=10) with ten repetitions. Compare the RMSE (or MAE) of the PLS-SEM results against a simple Linear Model (LM) benchmark. Predictive Power Tiers: High: PLS-SEM error < LM error for all indicators. Medium: PLS-SEM error < LM error for most/half of the indicators. Low: PLS-SEM error < LM error for a minority of indicators. None: PLS-SEM error is higher across the board.
5. **Model Comparison (Optional)**
   To choose between competing models, identify the one that minimizes the Bayesian Information Criterion (BIC) or the GM value. For further verification of a model's relative likelihood, calculate Akaike weights.

Application of SEM in Science and Technology Education

Intents of Using Structural Equation Modelling

There are four major intents of using SEM in a study. One intent of using SEM is in strict confirmatory sense, although somewhat rare in practice. In strict confirmatory intent, a researcher seeks to test a single a priori model and nothing more. There is no alternative/equivalent or near equivalent model to compare fit indices across. The researcher only accepts or reject the model. The question as to whether 'model fit adequate' as captured in Kline's (2016) framework is not necessary in confirmatory sense of SEM. 'The second intent of using SEM may be to evaluating the fit of a model in an absolute sense and comparing it with alternative models that reflect competing theoretical accounts or offer a more parsimonious account of the data' (Hoyle, 2012, p.8).

In the second intent, the researcher specifies all the equivalent models a priori before estimation of parameters. It must be noted that, just like every model specification, the equivalent models must be derived from sound theories or empirical evidences and must allow for statistical comparison to be made. The model with better or best fit is accepted over other competing models. The third intent of using SEM is for model generation. In fact, this is the intent to which SEM is used in many thesis works in Nigeria. The model generation could be in strict confirmatory or alternative analysis. The researcher using SEM for generation of model are at liberty to evaluate the model parameters and when the fits is poor, the model would be re-specified. In fact, the researchers often use SEM software to facilitate model re-specification. The ultimate aim of the researcher who use SEM to develop the most parsimonious models that will fit the observed data adequately. The fourth intent is the use of SEM to only understand the direct or the indirect effects of variables. In this sense, SEM-based softwares can be used in place of instead of regression-based software such as PROCESS Procedure for SPSS.

A number of researchers have applied SEM in education research. For instance, Voorhees et al. (2020) utilized CB-SEM to investigate factors that influence undergraduate students' achievement in Mathematics. The authors utilized CB-SEM against the recommendation that PLS-SEM is more appropriate when the intention is to develop a model. CB-SEM was also applied to examine the influence of psychosocial variables on students' efforts in Mathematics using upper primary government school students in Northern West Bank, Palestine (Daher et al., 2017). Similarly, an explanatory model of Mathematics achievement has also been developed using CB-SEM on a sample of 5^{th} and 6^{th} grade Spanish students in public primary school (Rodriguez et al., 2017). Furthermore, Nazim and Ahmad (2014) applied SEM in investigating the influential factors of 8^{th} Grade students' Mathematics achievement in Malaysia. Al-Agili et al. (2013) compared two models for describing causal relationship among affective variables and students' Mathematics achievement using CB-SEM approach in Libya. A similarly was carried out a study to test a comprehensive and a pervasive model for predicting students' Mathematics achievement (Ogbu et al., 2024: Badieeet al., 2013). In Isreal, Alhija and Amasha (2012) investigated the role of learners and learning environment characteristics in modelling achievement in Mathematics. Wang, Osterlind, & Bergin (2012) developed Mathematics achievement models of 8^{th} grader in four countries using data obtained from the Trends in International Mathematics and Science Study (TIMSS) 2003. The countries used in the students were USA, Russia, Singapore and South Africa. In Nigeria, factors impacting mathematics teachers' effective application ICT have been modelled (Ogbu, 2025)

Misapplications of SEM

SEM is one of the emerging statistical techniques that is widely being applied in education. However, despite the growing application of SEM, many researchers seem to abuse SEM,may be due to limited knowledge of the basic principle of SEM. The abuse of SEM is more common in VB-SEM distribution of data assumptions are relaxed.

In conducting SEM-based studies, the key first step involves extensive literature on the relationship between the variables that are studied. Specification of the relationships among variables should be guided by theory or empirical evidence. However, in most of the SEM studies, some researchers hardly explain, under their hypothesized models how the relationships come about. Therefore, specifying a model without adequate theoretical or empirical backup is an abuse of the basic assumptions of SEM-based studies. This abuse often arise because of shallow knowledge on how the variables are related.

The common abuse of VB-SEM is poor reporting of collinearity issue. Collinearity refers to high correlations between variables, implying that the variables are likely measuring the same construct. When there are more than two variable having high correlation coefficient, it is referred to as mult-collinearity. High correlation coefficient threating the internal validity of the study. As a rule of thumb, correlation coefficient between two variables should not exceed 6.0. Removing one of the variables or creating linear combination of the variables is often used to handle the problem of multicollinearity.

Another frequently misapplication of SEM is the use of small sample size. Although, VB-SEM are not affected much by the use of sample size, some researchers often use grossly small sample size even when they can have access to larger sample size. This abuse also cripple into CB-SEM thereby making the findings from some of these studies questionable. Whether VB-SEM or CB-SEM, the researcher should strive to use larger sample except in a situation where it is extremely impossible to obtain larger sample size.

Some researchers seem to be unsure of the type of hypotheses they test in SEM-based studies. It is common to see in doctoral thesis, especially from Nigeria containing hypothesis such as “there is no significant model fit between the hypothesized model and the empirical validate model” when the intention of the researcher was to develop a model. Unfortunately, most of these studies lacked appropriate parameters for comparing models, rather, they mere compare the model fit parameters of the two models. It is worth noting that most of the studies often establish that there is “no significant model fit between the hypothesized model and the empirical validate model” implying that the hypothesized model could as well replace the hypothesized. There is no point comparing hypothesized model and the empirical validated model if the intention of the research is to develop a theory and not to test a theory.

Conclusion

Structural Equation Modelling represents a powerful and flexible analytical framework that extends beyond the capabilities of traditional multivariate techniques such as multiple regression and ANOVA. Its capacity to simultaneously model measurement relationships and structural paths, incorporate latent variables, and estimate direct and indirect effects makes it particularly suitable for addressing complex theoretical questions in education and related fields. As discussed in this paper, SEM should not be viewed as a single statistical method but rather as a family of techniques that includes path analysis, confirmatory factor analysis, structural regression models, and latent change models, each serving distinct research purposes.

The distinction between covariance-based SEM and variance-based SEM is critical for appropriate model selection. While CB-SEM is best suited for theory testing and confirmation under stringent assumptions, PLS-SEM offers greater flexibility for prediction-oriented, exploratory, and complex models, especially when data distribution, sample size, or model structure pose challenges. It should be noted that flexibility in estimation should not be misconstrued as license for methodological laxity. Proper model specification grounded in theory or empirical evidence, careful evaluation of measurement and structural models, and transparent reporting of results remain essential regardless of the SEM approach adopted.

The paper also highlights recurring misapplications of SEM in educational research, including inadequate theoretical justification for hypothesized models, poor handling of collinearity, inappropriate sample sizes, and confusion regarding research intent and hypothesis testing. Such practices undermine the validity and interpretability of SEM findings and contribute to questionable conclusions. Therefore, researchers are encouraged to develop a solid understanding of SEM principles, clearly articulate the intent of their analyses, and adhere to established guidelines for model evaluation and reporting.

References

Adewale, J. G., Metibemu, M. A., Anyanwale, A. &Antia, A. I. (2020). *A practical course to on partial least square structural equation modeling: a step-by-step guide to practice*. EARNiA.

Al-Agili, M. Z. G., Mamat, M. B., Abdullah, M. L. &Maad, H. A. (2013). Two model of describing students' achievement in Mathematics: A comparative study. *Australian Journal of Basic and Applied Science, 7(6),* 184-198.

Alhija, F. N. &Amasha, M. (2012). Modeling achievement in Mathematics: The role of learner and learning environment characteristics. Educational Research and Evaluation. *An International Journal of Theory and Practice, 18(1),* Retrieved from https://doi.org/10.1080/13803611.2011.640862

Badiee, H., Babakhani, N. &Hashemian, K. (2013). The explanation of structural model of academic achievement based on perception of classroom structure and use of motivational strategies in middle schools of Tehran. *5th World Conference Education Sciences-WCES 2013. Procedia-Social and Behavioural Science, 116(2014),* 397-402.

Civelek, M. E. (2018). *Essential of structural equation modeling*. Zea E-books, Retrieved from .unl.edu/zeabook/64

Coolidge, F. L. (2006). *Statistics: A gentle introduction* (2nd ed.) New Delhi, 110047 India: Sage Publication.

Daher, W., Al-Khali, F., & Abu-Kayyas, Y.(2017). Psychological variables that affect students' effort in Mathematics. Retrieved from https://researchgate.net/publication/319044112_PSYCHOLOGICAL_VARIABLES_THAT

Gana, K. &Broc, G. (2019). *Structural equation modeling with lavaan*. London: ISTE Ltd.

Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Dank, N. P., & Ray, S. (2022). *Partial least squares structural equation modeling using R: A classroom companion*. Business Expert Press.

Hair, J. F., Hult, T., Ringle, C. M., &Sarstedt, M. (2018). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed.). Thousand Oaks: Sage.

Hoyle, R. H. (2012). *Introduction and review*. In R. H. Hoyle (Ed.). *Handbook of structural equation modeling*. New York: The Guilford Press.

Kline, R. B. (2016). *Principles and practice of structural equation modeling*. New York: The Guilford Press.

Knock, N. (2020). WarpPLS user manual: version7.0. ScriptWarp System.

Ogbu S. (2025). Modelling the Impacts of Teachers' Access, Motivation, Attitude, and Self-efficacy on Mathematics Teachers' Effective ICT Utilization in Classrooms. International Journal of Instruction, 18(2); 429-454. https://www.eiji.net/dosyalar/iji_2025_2_24.pdf

Ogbu, S. Ugwu, C. B. A., Ngwu, A. N., Aniaku, O. L, Ugwu, T. U., Nwakwo, A. L Abamuche, J. Ogbanufe, U. O. & Agugoesi, O. J. (2024). Modelling the Effects of Selected Sociological and Psychological Factors on Secondary School Students' Achievement in Mathematics. *Multicultural Education, 10*(5). https://doi.org/10.5281/zenodo.11223950

Ogbu, S. Ogbanufe, U. O., & Idika, E. O. (2023). Mechanism, use, and misuse of factor analysis: Re-examining the emerging issues in educational assessment in the 21st-century. In J. O. Oguniyi, L. Achimugu, C. G. Omachonu, K. O. Muraina, S. M. Enefu, E. A. Tolorunleke, & A. A. Musa (Eds.). Emerging Issues and Innovations in Educational Technology in the 21st-Century. Kano: Tunlad Prnts & Publishing Coy.

Risher, J., Sarstedt, M. &Ringle, C. M. (2018). When to use and how to report the results of pls-SEM. *European Business Review*, https://www.doi.or/10.1108/EBR-11-2018-0203

Rodriguez, S., Rneiro, I., Gomez-Taibo, M. L., Regueiro, B., Estevez, I &Vall, A. (2017). An explanatory model of maths achievement: Perceived parental involvement and academic motivation. *Psicothema, 29(2),* 184-190, https://doi.org/10.7334/psicothema2017.32

Sanchez, G. &Trinchera, L. (2013). plspm: partial least squares data analysis method. R package version 0.2-2. Retrieved from http://CRAN-R-project.org=plspm

Ullman, J. B. (2007). *Structural equation modeling*. In Tabacknik, B. G and Fidell, L. S. (Ed.). Using multivariate statistics (5th ed.). New York: Person.

Voorhees, C. M., Brady, M.K., Calantone, R. & Ramirez, E. (2016). Discriminant validity testing in marketing: an analysis, causes for concern, and proposed remedies. *Journal of the Academy of Marketing Science, 44(1), 119-134.*

Wang, Z., Osterlind, S. J. & Bergin, D. A. (2012). Building a Mathematics achievement models in four countries using TIMSS 2003. *International Journal of Science and Mathematics Education, 2012 (10), 1215-1242*