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Review Article

Tutorial on Structural Equation Modeling in Medical Research Manuscript Type: A Review Article

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Abstract
Structural equation modeling (SEM), as a quantitative approach, can greatly help the researcher in the analysis of multivariate experimental data. This issue can be more significant in medical research. The results of SEM are expected to be more realistic than those of the regression analysis. SEM is a combination of measurement and structural models. The measurement model in SEM is divided into two types of reflective and constructive indicators. Fitting indicators of measurement models (external model) include index reliability, convergent validity, and divergent validity. Structural model indices (internal model) include Significant numbers t (T - values), Coefficient of determination (R^2), The effect size (f^2), Predictive Relevance (Q^2 criterion), Quality Index, Communality Criterion (sharing index), and Redundancy Criterion. Overall fit indicators also include GOF criterion. In the present study, various methods and indicators of structural equation modeling have been developed in full detail, which can help researchers in conducting their studies in the field of structural equations.
Keywords: Structural equation modeling, Partial least squares approach (PLS-SEM), Fit evaluation indicators, Exploratory factor analysis, Confirmatory factor analysis

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Introduction

Structural equation modeling (SEM), as a quantitative approach, can greatly help the researcher analyze the multivariate experimental data. By using SEM, a theoretical model can be tested in general and in detail. In other words, not only modeling helps the researcher in testing univariate and bivariate hypotheses, but also multivariate hypotheses can be tested (1, 2).

SEM is a combination of measurement and structural models (3). Measurement models determine which observed variables or reagents measure which hidden variables, and structural models determined which independent variables affect which dependent variables and which variables are related to each other (4, 5).

Modeling with the help of a researcher to explain cultural and social phenomena has a considerable potential. Whether the collected data is cross-sectional or longitudinal, modeling allows the researcher to formulate and evaluate various relationships between different variables based on the theoretical framework, empirical background as well as personal views. The ways in which the variables affect each other and the intensity and direction of the impact are among the common cases that are addressed in modeling. This principle states if the input data can be reproduced using the formulated model and the parameters estimated based on the same data, it means that the model can be considered acceptable (6).

For clarification of the difference between modeling and conventional statistical methods, suppose a research situation in which a researcher tends to estimate the impact factor of one latent variable on another variable. In SEM, the coefficient of the influence of one latent variable on another variable is calculated in a state, and its difference is estimated to be zero; at the same time, their measurement models and measurement error are present (7, 8).

In the usual methods for statistical analysis, the researcher follows a path according to which in the first stage he/she is highly confident that the designed scales have the desired measurement accuracy scientifically. In the second step, the researcher calculates the score of each respondent in two main hidden variables. In the third step, he/she estimates the standardized beta by using simple linear regression and placing one variable as the dependent variable and the other as the independent variable and determines whether the research hypothesis that the independent variable affects the dependent one is correct (9, 10). The results of structural equation modeling are expected to be more realistic than thoseof regression analysis. Methodologically, it is expected that more accurate results will be obtained when estimating the standardized beta parameter, even if the measurement error of the latent variables is taken into account (11).

Structural equation modeling (SEM), as a quantitative approach, can greatly help the researcher in the analysis of multivariate experimental data. This issue can be more significant in medical research. The aim of the present study was to present various methods and indicators of structural equation modeling with complete details, which can help researchers in conducting their studies in the field of structural equations.

Types of Variables in SEM

There are different types of variables in designing SEM. Knowing the type of these variables and the way to identify them could help the researcher to compile the model comprehensively. Variables can be examined from different perspectives such as their scale, their role in modeling, and their observability/invisibility (12). Definition of all types of these variables is presented in the following sections.

Classification of Variables According to Scale

Quantitative variable: Variables that can be measured to assign numbers to the subject status and according to a certain rule are divided into two continuous and discrete types. For example, blood pressure is a continuous variable that can contain decimal values between two intervals, whereas between two intervals of a discrete variable, no other value can be found, such as the number of Rotten teeth (13). Interval scales are numbers that represent quantity in numerical units and based on an independent scale. Height and weight are good examples of quantitative data. At this scale, the zero point is conventional, such as temperature. The difference between this scale and the previous one is in having the origin (zero point). In this way, in addition to the ability to rank, it is possible to identify the differences between different items in terms of the attribute of the desired variable.

Qualitative variables: These variables include various modes of a feature such as gender, religion, occupation, etc. (14). Nominal scale related to qualitative properties or membership in a specific group. Nominal data represents categories or labels without any numerical or hierarchical order. The labels can be represented by numbers, letters, or other symbols, but the form of representation does not change the nature of the data such as blood type, gender, and marital status. Ordinal scale includes ranks, belonging to ranked groups or sequential information such as scale 1 to 10 or Likert scale 5 and 7 options.

Classification of variables according to their role in the model: This classification includes independent or exogenous variable, dependent or endogenous variable, mediating variable, moderating variable, control variable, and annoying or confounder variable as follows:

Independent or Exogenous variable: It is a variable that positively or negatively affects the dependent variable. In modeling structural equations, independent variables are called exogenous variables because the cause-and-effect relationship starts from these variables and the direction of the arrow is drawn from these variables. In fact, exogenous variables are those whose changes are influenced by the factors that are outside the model (15, 16).

Dependent and Endogenous variable: It is a variable whose changes are affected by the independent variable. In modeling structural equations, dependent variables are called endogenous variables because the cause-and-effect relationship leads to these variables and the direction of the arrow is drawn to these variables (17). In other words, endogenous variables are those whose changes are explained by external and internal variables of the path diagram. If a variable has a share in the relationship between two independent and dependent variables, it has acted as a mediating variable (18). For example, in examining the relationship between daily salt consumption and blood pressure, salt consumption is the independent variable and blood pressure is the dependent variable.

Mediator variable: It is a variable that modulates (more or less) the direction or intensity of the relationship between the independent and dependent variables (19). The study of moderating variables in research helps to formulate the model more appropriately because if this type of variable is not studied, the relationship between research structures is interpreted incompletely. The interactive effect (multiplication) between the main independent variable and the moderator variable on the dependent variable is also shown in the model (20).

Confounder variable: It is a variable whose effect on the relationship between the two variables is not desired by the researcher and does not want to include this effect in his research. Therefore, it tries to neutralize this variable by controlling it. The reason for this is that the effect of all research variables cannot be studied simultaneously and we have to neutralize the effect of some of them (21).

Moderator: It is a variable that exists; it cannot be seen, heard, or felt, but it can be inferred from behavior such as inheritance (22). In fact, it is not possible to observe this variable directly, and its effect cannot be controlled. In the case of intervention variables, the researcher should consider their role in interpreting the results and analyze their impact. For example, job satisfaction of employees may be affected by inflation and high prices in society because these factors may affect job satisfaction of employees. However, it is not under our control, so inflation and high prices is a disturbing variable in this study.

Classification of Variables According to Observability or Invisibility

Observable variables: These are variables that can be measured directly (23). For example, people's height can be determined directly using measuring tools. In fact, these variables are the same questions or indicators of the questionnaire (24, 25).

latent variables: latent variables, unlike observable variables, cannot be measured directly and must be measured using their indicators or criteria (26). Consider, for example, the financial performance of an organization that cannot be measured directly using specific tools (27). It is important to note that latent variables in SEM come in the form of ellipses or circles, and observable variables in the form of rectangles or squares (28). If the measurement model is reflective, the direction of the arrows is from the hidden variable to its indicators. However, if the measurement model is of the constructor type, the direction of the arrows is plotted from explicit variables to latent variables (29).

SEM Components

Reflective and formative are two types of measurement models used in SEM. In these two types of measurement models, latent variables and all hypothesized dependencies are measured based on path analysis, respectively. There are different types of measurement model that will be mentioned in the next section. Based on whether the direction of the arrows (Dag) is observed from the side of the latent variable to the side of observed variable or vice versa, there are two types of models with the names of reflective and formative, respectively. Both reflective and formative models have their own applications and suitability based on the research context (30, 31).

The Covariance Matrix is a matrix whose members show correlations between different system parameters. One of the distinguishing features of SEM from other statistical methods is that this technique uses the structure of covariance for analysis. In SEM, covariance between variables , is used to analyze the data (32). Thus, one of the ways to enter data into SEM software such as LISREL is to use the covariance matrix between variables. Researchers use SEM software frequently to identify and use a useful process called path analysis to estimate and interpret the relationships.

Path analysis is a technique that uses dual relations to estimate the relationships in structural equation models. SEM primarily focuses on estimating the relationships between endogenous variables and may not explicitly estimate the correlations between exogenous variables (33).

Briefly, SEM is one of the widely used methods in behavioral science studies to test the models in their power of explaining and predicting the behaviors (34).

Types of Matrices in Estimating Relationships in Structural Equation Modeling

Observed Covariance Matrix: This matrix consists of actual and observed values of variance and covariance between model structures.

Estimated Covariance Matrix: This matrix contains the predicted values of variance and covariance of the research structures. In fact, the values expected to be obtained from the relationship between the structures will be shown in this matrix.

Residual Matrix: This matrix contains values obtained by subtracting the values of the observed matrix and the estimated matrix. In fact, the remaining matrix shows the difference between our forecast and the actual values obtained from the collected data. The important point is that the lower the values of this matrix, the better the fit of the model and the closer the model is to reality.

First- and Second-Generation SEM

Covariance-based SEM: Covariance-based SEM methods were first introduced by Karl Jöreskog and Dag Sörbom in the 1970s, specifically through the development of the LISREL (Linear Structural Relations) software (35). In this method, the coefficients of paths and factor loadings are estimated using the minimization of the difference between the observed and predicted variance-covariance matrices. The most widely used method of calculating coefficients in first generation methods is the Maximum Likelihood Estimate approach, which requires data on the observed variables, which must have followed a normal distribution (36, 37).

Partial Least Square (Component-Based Models)

Partial Least Square (PLS) was invented by Weld (1974) (38). The PLS method includes two main steps: 1) examining the fit of measurement and structural models, and 2) testing the relationships between the constructs. Now the question is which of the SEM approaches is better to use and which of them have correct and valid results.

One way for selecting SEM methods is the existence of hidden variables with constructive indicators in the research model. If the researcher model contains these variables, we have to use the SEM method because such a capability is not defined in the first-generation approaches and consequently software such as LISREL and AMOS are unable to draw structures with constructive indicators. Another way is related to the existence of hidden variables of the second order in the research model. These types of variables are used when the researcher uses a hidden variable in more than two levels. In this case, it would be better for him to use the SEM method. Of course, first-generation methods are also able to implement such models, but the researcher must use all the hidden variables in the first level if using first-generation methods.

For finding latent variables, one method is to use factor analysis (FA). Exploratory (EFA) and confirmatory (CFA) are two main types of FA. In SEM, the combination of confirmatory FA and path analysis is used. In the following section, two types of FA are briefly mentioned. FA is used to understand the underlying variables (latent variables) of a phenomenon or data reduction. The primary data for FA is the correlation matrix between variables. FA does not have predefined dependent variables (39).

EFA is a method used to find latent structure and data reduction. EFA is a method that can justify the overlap of variables without sufficient evidence for researchers. (40, 41)exploratory structural equation modeling (ESEM. CFA is based on pre-experimental data that can be a specific classification scheme for subtests. An important difference between EFA and CFA methods is that the method determines the correlation matrix with the most cost-effective method of explaining the common underlying variance. However, confirmatory methods determine whether the data are consistent with a certain factor structure or not. In confirmatory analysis, a model is constructed in which it is assumed that experimental data are described or calculated based on several parameters (42).

SEM with Partial Least Squares Approach (PLS-SEM)

SEM with PLS-SEM was invented by Weld (1947) and later a more advanced version of this method by Lemoler (1989) was presented (43). PLS is one of the second generation approaches and has advantages compared to the previous methods. One of the reasons for the popularity of the PLS method is that it does not use a large sample size, while the previous methods had an immediate need for a high number of samples (N>200). PLS is insensitive to sample size to such an extent that even the number of samples can be less than the total number of research variables. (43).

Rules for Selecting the Type of Measurement Models in Structural Equations

One of the most comprehensive methods that authors use to select the type of measurement models is the four-law method by Jarvis et al. (2003) (44, 45).

Cause-and-effect relationship: For this relationship in the constructor model, it is drawn from index to structure, while in the reflective model, this direction is from constructor to index. This rule itself consists of three sub-rules in the following order: a) In the constructive model, indicators are the defining factors (constructs) of the structure, while in the reflective model indicators are the features that arise from the existence of the structure; b) In the constructive model, a change in the indices will certainly cause a change in the structure, while in the reflective model, a change in the indices does not necessarily lead to a change in the structure; and c) In the constructive model, a change in the structure does not cause a change in the indices, while in the reflective model, any change in the structure causes a change in the indices.

Cross-correlation between indicators: In the constructive model, the cross-correlation between indicators is not clarified. This rule consists of two sub-rules: I) In the reflective model, the indicators reflect the same (or similar) concept, while this rule is not certain in the case of the constructive model; II) In the constructive model, the removal of one of the indicators may change the concept of the structure and make its definition incomplete, while in the reflective model, in the case of the removal of an index, the concept of the structure should not be significantly changed.

Simultaneous change of indicators together: In the constructive model, making a change in one indicator cannot lead to a change in other indicators while in the reflective model, a change in one index can cause changes in other indices.

Predictions and consequences of indicators of a structure: In the constructivist model, indicators do not have the same consequences, while in the case of reflective models, the indicators have the same consequences.

Model Evaluation Criteria (Measurement Model, Structural Part and General) in Structural Equation Modeling

The method for evaluating structural equation models consists of three parts: 1) the part related to measurement models (external models), 2) the structural part (internal model), and 3) the general part (measurement and structural). It is important to note that the structural relationships are meaningful when the values of the measurement models are acceptable (46, 47). All these criteria are mentioned one by one in the following sections. Model evaluation criteria in SEM are also shown in Figure 1.

Fit Evaluation Indices of Measurement Models

For examining the fit of measurement models, three types of indices are used:

Reliability and Validity Based Indices

Cronbach's alpha: Internal consistency indicates the degree of correlation between a construct and its related indicators. A high value of variance can indicate high internal stability. Cronbach's alpha above 0.7 means adequate reliability (48).

Combined Reliability (CR): CR of a structure is obtained from a ratio; in the case of this fraction, the variance between a structure with its indices and in the denominator of the fraction, the variance of the structure with its indices is added to the measurement error (49).

Convergent validity: It is the relationship of the structure with the variables of the hypothesis and theoretical foundations. In fact, there are times when the scores obtained from the two tools on a concept are highly correlated. The AVE criterion represents the average variance shared between each structure and its indices (50).

Divergent validity: With the divergent validity, the degree of the relationship of a structure with its indicators can be investigated in comparison with other indicators.(50, 51).

Structural Models Indices

Significant numbers t (T-values): In structural models, t-values are commonly used to determine the statistical significance of individual path coefficients or regression weights. While a threshold of 1.96 may be applicable in some cases,

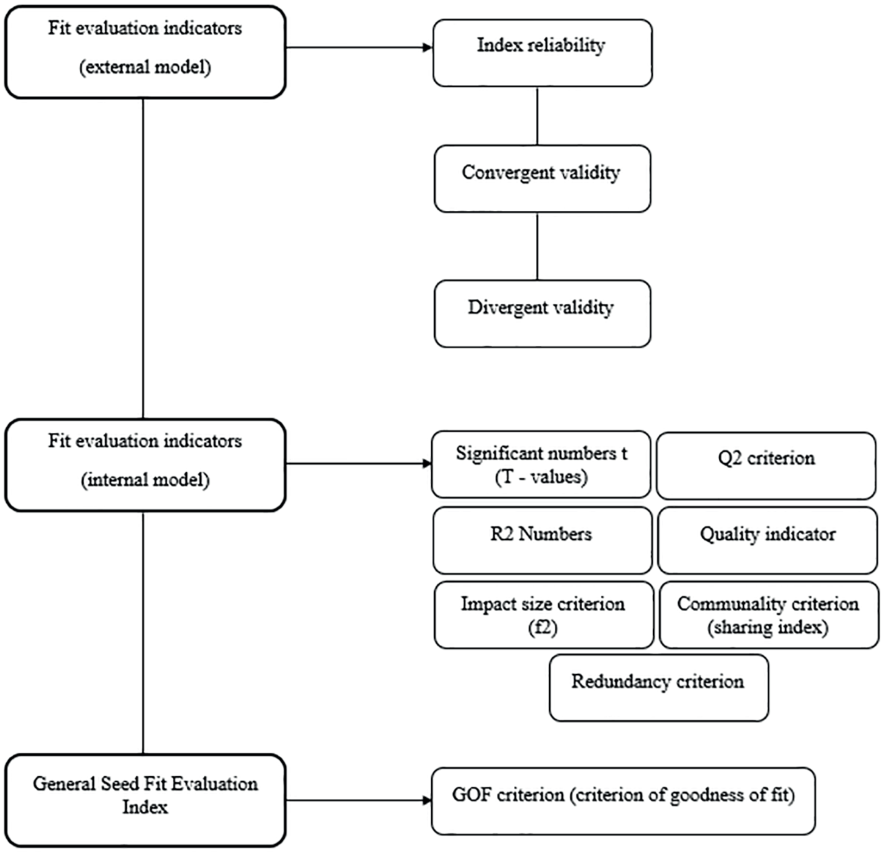

Figure 1: Model evaluation criteria in structural equation modeling

it is not a universal criterion for all structural models. The significance level for t-values depends on the desired statistical confidence level (e.g., 95%) and the sample size (52).

Coefficient of determination (R^2): This criterion can be used to connect the measurement part and the structural part, and it shows the effect that an exogenous variable has on an endogenous variable. A value higher than 0.6 indicates a suitable value for this criterion (53).

The effect size (f^2): This criterion was introduced by Cohen (1988) and determines the intensity of the relationship between the structures of the model. It should be noted that the values of 0.02, 0.15, and 0.35 indicate the small, medium, and large size of a structure (54).

Predictive Relevance (Q^2 criterion): This criterion can determine the model's prediction power. Hensler et al. (2009) have determined the severity of model prediction for endogenous structures as three values of 0.02, 0.15, and 0.35. This means that the prediction of the model has a small, medium, and large prediction power, respectively (55).

Quality indicator: According to the structure of PLS modeling, it is necessary to optimize each part of the model. For this reason, in PLS path modeling, three different indices for model fit are provided: sharing index, redundancy index, and goodness of fit index (GOF) (56).

Communality criterion (sharing index): The quality of measurement models in PLS method is evaluated using communality criterion. This criterion for each index is obtained through the mean of the second-order values of the relationship between that index and its own structure, which are the same as the factor loads. Positive values of this index indicate acceptable measurement values (57).

Redundancy criterion: This criterion can measure the quality of the structural model and show the variability of the indices of an endogenous structure. The positive values of this index indicate the acceptability of the measured values (58).

General Goodness of Fit Evaluation Index

The overall goodness of fit (GOF) indices represent the general part of the SEMs. GOFs are obtained by multiplying the average values of the joint values of each structure by the average values of R^2 of endogenous structures of the model (R2) (59) (Figure 2).

Fit indicators are presented in Table 1.

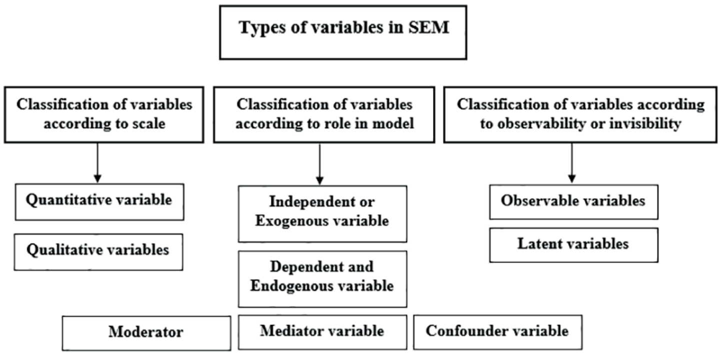

Figure 2: Types of variables in SEM

Table 1: Model-Fit Criteria and Acceptable Fit Interpretation

	Model-fit Criterion	Acceptable Level	Interpretation
1	Chi-Square	<5.0	Compares obtained X^2 value with tabled value for given DF
2	Goodness-of-fit index (GFI)	>0.90	Value close to 0.90 or 0.95 reflects a good fit
3	Adjusted GFI (AGFI)	>0.85	Value adjusted for DF, with 0.90 or 0.95 a good model fit
4	Root-mean square residual (RMR)	<0.08	Indicates the closeness of ∑ to S matrices
5	Standardized RMR (SRMR)	<0.05	Value less than 0.05 indicates a good model fit
6	Root-mean square error of approximation (RMSEA)	<0.08	Value of 0.05 to 0.08 indicates close fit
7	Tucker-Lewis Index (TLI)	>0.90	Value close to 0.90 or 0.95 reflects a good model fit
8	Normed fit Index (NFI)	> 0.90	Value close to 0.90 or 0.95 reflects a good model fit
9	Parsimony fit index (PNFI)	>0.50	Compares values in alternative models

Software Guideline

Some of the most widely used software packages for SEM are SPSS, AMOS, LISREL, Mplus, R, and STATA. Each of these packages has its own advantages and disadvantages, depending on your research objectives, data characteristics, model complexity, and technical skills. IBM SPSS Amos lets you easily use structural equation modeling (SEM) to test hypotheses on complex variable relationships and gain new insights. This module is a stand-alone application and does not require SPSS Statistics.

Conclusion

Structural equation modeling (SEM), as a quantitative approach, can greatly help the researcher in the analysis of multivariate experimental data. This issue can be more significant in medical research. The results of SEM are expected to be more realistic than those of regression analysis. Briefly, SEM is one of the widely used methods in behavioral science studies to test the models in their power of explaining and predicting the behaviors. In the present study, various methods and indicators of structural equation modeling have been developed in full detail, which can help researchers in conducting their studies in the field of structural equations. In this study, various types of matrices are mentioned in the estimation of the relationships in SEM, including the Observed Covariance Matrix, Estimated Covariance Matrix, and Residual Matrix. For checking the fit of the measurement models, three types of indicators, such as Reliability and Validity based indices, Structural models indices, and General Seed Fit Evaluation Index, are used. The indicators of the structural models mentioned in the present study are Significant numbers t, Coefficient of determination, the effect size, Predictive Relevance, Quality Index, Communality Criterion, and Redundancy Criterion.

Authors' Contribution

S.B. and F.M. conceived of the presented idea. S.B. wrote the manuscript with support from F.M. All authors read the manuscript and verified it.

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References

1. Xiong B, Skitmore M, Xia B. A critical review of structural equation modeling applications in construction research. *Automation in construction*. 2015;49:59-70.

2. Henseler J. Bridging design and behavioral research with variance-based structural equation modeling. *Journal of advertising*. 2017;46(1):178-92.
3. Collier J. Applied structural equation modeling using AMOS: Basic to advanced techniques: Routledge; 2020.
4. Hair Jr JF, Howard MC, Nitzl C. Assessing measurement model quality in PLS-SEM using confirmatory composite analysis. *Journal of business research*. 2020;109:101-10.
5. Iacobucci D. Structural equations modeling: Fit indices, sample size, and advanced topics. *Journal of consumer psychology*. 2010;20(1):90-8.
6. Heck R, Thomas SL. An introduction to multilevel modeling techniques: MLM and SEM approaches: Routledge; 2020.
7. Loehlin JC. Latent variable models: An introduction to factor, path, and structural equation analysis. London: Psychology Press; 2004.
8. Henseler J, Chin WW. A comparison of approaches for the analysis of interaction effects between latent variables using partial least squares path modeling. *Structural equation modeling*. 2010;17(1):82-109.
9. Keith TZ. Multiple regression and beyond: An introduction to multiple regression and structural equation modeling: Routledge; 2019.
10. Cheung MW. Modeling dependent effect sizes with three-level meta-analyses: a structural equation modeling approach. *Psychol Methods*. 2014;19(2):211-29. doi: 10.1037/a0032968.
11. Rosseel Y. Small sample solutions for structural equation modeling. Small sample size solutions: Routledge; 2020. p. 226-38.
12. Sovacool BK, Axsen J, Sorrell S. Promoting novelty, rigor, and style in energy social science: Towards codes of practice for appropriate methods and research design. *Energy research & social science*. 2018;45:12-42.
13. Asmus EP, Radocy RE. Quantitative analysis. Critical essays in music education: Routledge; 2017. p. 129-72.
14. Kim JH, Kim AR, Kim MG, Kim CH, Lee KH, Park D, et al. Burnout Syndrome and Work-Related Stress in Physical and Occupational Therapists Working in Different Types of Hospitals: Which Group Is the Most Vulnerable? *Int J Environ Res Public Health*. 2020;17(14). doi: 10.3390/ijerph17145001.
15. Waheed SA, Khader PSA. Healthcare solutions for children who stutter through the structural equation modeling and predictive modeling by utilizing historical data of stuttering. *SAGE Open*. 2021;11(4):21582440211058195.
16. Al-Mekhlafi A-BA, Isha ASN, Chileshe N, Abdulrab M, Kineber AF, Ajmal M. Impact of safety culture implementation on driving performance among oil and gas tanker drivers: a partial least squares structural equation modelling (PLS-SEM) approach. *Sustainability*. 2021;13(16):8886.
17. Puspita AWY, Suharyanto A, Indradi W. Risk management rework and repair implementation phase in building project to improve project quality performances. *International research journal of advanced engineering and science*. 2019;4(2):525-9.
18. Al-Kofahi ZG, Mahdavian A, Oloufa A. System dynamics modeling approach to quantify change orders impact on labor productivity 1: principles and model development comparative study. *International journal of construction management*. 2022;22(7):1355-66.
19. Özdil SÖ, Kutlu Ö. Investigation of the mediator variable effect using BK, sobel and bootstrap methods (mathematical literacy case). *International Journal of Progressive Education*. 2019;15(2):30-43.
20. Abadiyah R, Eliyana A, Sridadi AR. Motivation, leadership, supply chain management toward employee green behavior with organizational culture as a mediator variable. *International Journal of Supply Chain Management*. 2020;9(3):981-9.
21. Weyerhauser P, Kantelhardt SR, Kim EL. Re-purposing Chloroquine for Glioblastoma: Potential Merits and Confounding Variables. *Front Oncol*. 2018;8:335. doi: 10.3389/fonc.2018.00335.
22. Kaur L, Mittal R. Variables in Social Science Research. *Indian Res J Ext Edu*. 2021;21(2&3):64-9.
23. Curado MA, Teles J, Maroco J. [Analysis of variables that are not directly observable: influence on decision-making during the research process]. *Rev Esc Enferm USP*. 2014;48(1):149-56. doi: 10.1590/s0080-

623420140000100019.
24. Cooper B, Eva N, Fazlelahi FZ, Newman A, Lee A, Obschonka M. Addressing common method variance and endogeneity in vocational behavior research: A review of the literature and suggestions for future research. *Journal of vocational behavior*. 2020;121:103472.
25. McKenna SP, Heaney A, Wilburn J, Stenner AJ. Measurement of patient-reported outcomes. 1: The search for the Holy Grail. *J Med Econ*. 2019;22(6):516-22. doi: 10.1080/13696998.2018.1560303.
26. Treier S, Jackman S. Democracy as a latent variable. *American Journal of Political Science*. 2008;52(1):201-17.
27. Abowitz DA, Toole TM. Mixed method research: Fundamental issues of design, validity, and reliability in construction research. *Journal of construction engineering and management*. 2010;136(1):108-16.
28. Byrne BM. Structural equation modeling with EQS: Basic concepts, applications, and programming: Routledge; 2013.
29. Yazdani A, Lu L, Raissi M, Karniadakis GE. Systems biology informed deep learning for inferring parameters and hidden dynamics. *PLoS Comput Biol*. 2020;16(11):e1007575. doi: 10.1371/journal.pcbi.1007575.
30. Tarka P. An overview of structural equation modeling: its beginnings, historical development, usefulness and controversies in the social sciences. *Qual Quant*. 2018;52(1):313-54. doi: 10.1007/s11135-017-0469-8.
31. Holbert RL, Stephenson MT. Structural equation modeling in the communication sciences, 1995–2000. *Human Communication Research*. 2002;28(4):531-51.
32. Fisher TD. The relationship between perceived inclusion and the imposter phenomenon as mediated by work and gender identities in South Africa: University of Johannesburg (South Africa); 2019.
33. Xia Y, Yang Y. RMSEA, CFI, and TLI in structural equation modeling with ordered categorical data: The story they tell depends on the estimation methods. *Behav Res Methods*. 2019;51(1):409-28. doi: 10.3758/s13428-018-1055-2.
34. Ashoori F, Karimi M, Mokarami H, Seif M. Using health belief model to predict oral health behaviors in girl students: A structural equation modeling. *Pediatric Dental Journal*. 2020;30(1):24-32.
35. Jöreskog KG, Sörbom D. LISREL 8: User's reference guide, scientific software international. *Inc, Chicago*. 1996.
36. Kock N. From composites to factors: B ridging the gap between PLS and covariance-based structural equation modelling. *Information Systems Journal*. 2019;29(3):674-706.
37. Frega JR, Ferraresi AA, Quandt CO, Da Veiga CP. Relationships among knowledge management, organisational innovativeness and performance: Covariance-based versus partial least-squares structural equation modelling. *Journal of Information & Knowledge Management*. 2018;17(01):1850008.
38. Nevado JB, Flores JR, Penalvo GC. Simultaneous spectrophotometric determination of ethinylestradiol and levonorgestrel by partial least squares and principal component regression multivariate calibration. *Analytica chimica acta*. 1997;340(1-3):257-65.
39. Schreiber JB. Issues and recommendations for exploratory factor analysis and principal component analysis. *Res Social Adm Pharm*. 2021;17(5):1004-11. doi: 10.1016/j.sapharm.2020.07.027.
40. Morin AJ, Myers ND, Lee S. Modern factor analytic techniques: Bifactor models, exploratory structural equation modeling (ESEM), and bifactor-ESEM. *Handbook of sport psychology*. 2020:1044-73.
41. Zeynivandnezhad F, Rashed F, Kanooni A. Exploratory factor analysis for TPACK among mathematics teachers: Why, what and how. *Anatolian journal of education*. 2019;4(1):59-76.
42. McNeish D, Wolf MG. Dynamic fit index cutoffs for confirmatory factor analysis models. *Psychological Methods*. 2023;28(1):61.
43. Hair Jr JF, Hult GTM, Ringle CM, Sarstedt M, Danks NP, Ray S. Partial least squares structural equation modeling (PLS-SEM) using R: A workbook: Springer Nature; 2021.
44. Bollen KA, Paxton P. Interactions of latent variables in structural equation models. *Structural Equation Modeling: A Multidisciplinary Journal*. 1998;5(3):267-93.
45. Bollen K, Lennox R. Conventional wisdom on measurement: A structural equation

perspective. *Psychological bulletin*. 1991;110(2):305.
46. West SG, Taylor AB, Wu W. Model fit and model selection in structural equation modeling. *Handbook of structural equation modeling*. 2012;1(1):209-31.
47. Bagozzi RP, Yi Y. On the evaluation of structural equation models. *Journal of the academy of marketing science*. 1988;16:74-94.
48. Tavakol M, Dennick R. Making sense of Cronbach's alpha. *Int J Med Educ*. 2011;2:53-5. doi: 10.5116/ijme.4dfb.8dfd.
49. Guo Y, Gao H, Wu Q. A combined reliability model of VSC-HVDC connected offshore wind farms considering wind speed correlation. *IEEE Transactions on Sustainable Energy*. 2017;8(4):1637-46.
50. Russell JA. Evidence of convergent validity on the dimensions of affect. *Journal of personality and social psychology*. 1978;36(10):1152.
51. Carlson KD, Herdman AO. Understanding the impact of convergent validity on research results. *Organizational Research Methods*. 2012;15(1):17-32.
52. Burns JC, On D, Baker W, Collado MS, Corwin JT. Over half the hair cells in the mouse utricle first appear after birth, with significant numbers originating from early postnatal mitotic production in peripheral and striolar growth zones. *J Assoc Res Otolaryngol*. 2012;13(5):609-27. doi: 10.1007/s10162-012-0337-0.
53. Piepho HP. A coefficient of determination (R(2)) for generalized linear mixed models. *Biom J*. 2019;61(4):860-72. doi: 10.1002/bimj.201800270.
54. Chuan CL, Penyelidikan J. Sample size estimation using Krejcie and Morgan and Cohen statistical power analysis: A comparison. *Jurnal Penyelidikan IPBL*. 2006;7(1):78-86.
55. Chin W, Cheah J-H, Liu Y, Ting H, Lim X-J, Cham TH. Demystifying the role of causal-predictive modeling using partial least squares structural equation modeling in information systems research. *Industrial Management & Data Systems*. 2020;120(12):2161-209.
56. Tenenhaus M, Vinzia YC, Lauro C. PLS Path Modeling Computational Statistics & Data Analysis, v. 48. 2005;48(1):159-205.
57. Ximénez C, Maydeu-Olivares A, Shi D, Revuelta J. Assessing cutoff values of SEM fit indices: Advantages of the unbiased SRMR index and its cutoff criterion based on communality. *Structural Equation Modeling: A Multidisciplinary Journal*. 2022;29(3):368-80.
58. Li Y, Gu X. Feature selection for transient stability assessment based on improved maximal relevance and minimal redundancy criterion. *arXiv preprint arXiv:190301907*. 2019.
59. Purwanto A. Partial least squares structural squation modeling (PLS-SEM) analysis for social and management research: a literature review. *Journal of Industrial Engineering & Management Research*. 2021.