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Application of Structural Equation Modeling in Quantitative Research

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Abstract
The key aim of this study is to explore Structural Equation Modeling [SEM] is a more powerful statistical method for quantitative research. We applied document analysis method by using both latent and observable variables in comprehensive models where SEM makes it clear to examine intricate correlations between variables. SEM makes the collected data possible for academics to assess theoretic models. It also covers the benefits of SEM over the conventional statistical techniques such as making capacity to manage measurement error, take the latent variables into account, and examine intricate chains of causality. Nonetheless these difficulties, SEM delivers scholars with a flexible tool for developing new models and theories and grasping intricate phenomena in quantitative research. SEM offers a big framework for modeling of complex interactions that which advances in research of various domains in mathematics and statistics as well as public health, economics, psychology and sociology.

***Keywords**:* Quantitative research, structural equation modeling, explanatory factor analysis, confirmatory factor analysis, direct and mediating effects.

Introduction
In twenty first century, the structural equation modeling [SEM] is a significant statistical method used to estimate associations among the given independent and dependent variables (Ruiz et al., 2010). Structural Equation Modeling combines the dimensions different factors and multiple regression into a single framework, allowing scholars to assess both measurement models (relationships between both observed and latent variables as well as their construct, structural models) (Hair et al., 2021). It is also similar as multiple regression and factor analysis but it has certain advantages over these

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methods as well such as a useful approach for handling multi-collinearity and strategies for the accounting for response of data unreliability (Bielby & Hauser, 1977). This statistical method aims to represent hypotheses or premises which is observed the given data over average, variances and covariances in terms a smaller number of parameters defined by an underlying theoretical and conceptual model that is estimated (Martynova et al., 2018). It is a framework for posing sophisticated data-related queries utilizing statistical techniques and it minimizes dependence on a single statistic chi-square test, which was the primary tool used for application program for this statistical technique and offer a number of goodness of fit and comparative of fit statistics for model testing (Markus, 2012). The SEM approach seems to be playing a more and bigger part in advancing information for the field of mathematical study.

Moreover, researcher has to use statistical techniques to examine the available data and make decision is grounded on the characteristics of the data as well as own preferences and comprehension of the various approaches (Chau, 1997; Kline, 2023). Consequently, SEM makes the argument for why SEM is superior to alternative statistical methods because SEM is single of the most widespread statistical approaches used by mathematics and societal science researchers (Barrett, 2007). SEM Has been demonstrated to be more appropriate than multiple regression analysis and the multivariate technique when it takes to investigate numerous dependent connections at once (Collier, 2020). It (SEM) has robust logical skills for modelling complicated connections among variables; it is extremely pertinent in both mathematics and quantitative research. Furthermore, it is a potent method in mathematics that supports to validate and test theoretic models (Hair et al., 2021).

Structural Equation Modeling affords an outline for using empirical data to conform and improve mathematical constructions. It also agrees scholars to simultaneously analyze numerous variables and their correlations. Moreover, it also allows for the researchers to evaluate and validate theoretical frameworks in quantitative research spanning fields including economics, psychology, sociology and other social sciences disciplines. SEM is a particularly useful for research complex phenomena where causal connections need to be clarified because of its capacity to include latent variables and measurement error adjustments, which improve statistical analysis precision. As a consequence, SEM helps dynamic association in the combination of theoretical models and empirical findings, which bids a strict methodological framework that enhances both quantitative research methods and mathematical theory.

The main objective of the study is to use and apply structural equation modeling for fundamental ideas involved in quantitative statistical approach. Quantitative research is expected to benefit both novice researchers and those who have just used the tool for one study and wish to learn about the other features for which there was no requirement at the time. Creating a model that uses symbols to describe the relationships between variables in structural equation modelling, and it is a useful tool for researchers trying to conceptualize and comprehend events, particularly in mathematics' research.

Expectations of Structural Equation Modeling [SEM]

Generally, the structural equation modeling [SEM] adopts the data follows multivariate nomal supply, with dependent variables being continuous, though independent variables are not bound in normal distribution. Linear relationships among variables are essential, and maximum likelihood estimation is typically used for accurate results, though alternatives are acceptable. SEM requires complete data, as missing data can affect the analysis (Hair et al., 2019). There should be no multicollinearity, as strong correlations between variables can complicate evaluating their effects. Additionally, SEM demands a larger sample size compared to other methods and assumes that each construct measured is unidimensional, capturing a single concept.

Strengths of Structural Equation Modeling

In this context, structural equation modeling [SEM] refers the data analysis method that is often used in a range of academic topics due to its many advantages. First, one can manage measurement errors, second is using mediating variables is easily, and lastly, a statistical estimation of the theoretic model may be conducted (Kang & Ahn, 2021). Put another way, the researcher can determine whether to accept the theoretical model they have developed as accurate or make the necessary adjustments based on how well it matches the actual data. Comparing structural equation modelling to other methods, its main benefits are as follows: it enables us to investigate the effect of conjecturer variables on multiple dependent variables at the same time; it addresses measurement error in relationship prediction; and it can test the entire model rather than just specific relationships (Collier, 2020). This stands in stark contrast to related methods like as regression, which are limited to testing a single dependent variable at a time, do not take measurement error into consideration, and concentrate on individual associations rather than the group as a whole.

Variables

Mainly the variables in structural equation modeling [SEM] have been classified as latent variables, which are abstract constructs that are inferred from the observable variables. Similarly, observed variables which are directly measured by the researchers during

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their research. Additionally, structural equation modeling makes difference between exogenous variables, which have no effect over other factors but have the ability to influence others, and endogenous variables, which are impacted by other variables inside the modeling.

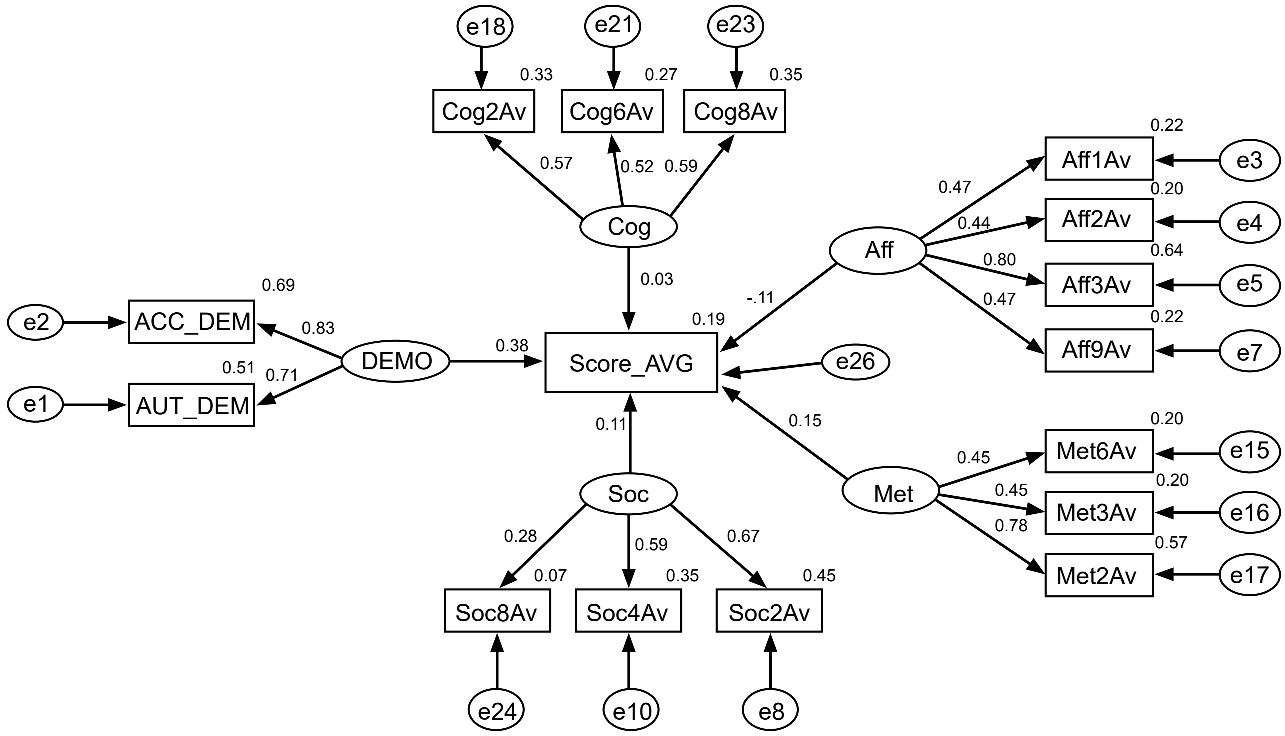
In quantitative research, latent variables refer the seen variables rather than being explicitly measured. Moreover, we can take the examples of observed variables are survey answers and taking test scores. Latent variables, such as contentment of intellect are abstract notation or constructions. Not only this, many scholars can test intricate theoretical models with direct and indirect effects by connecting these such variables over their routes which suggests potential links. Main variables are given below.

Manifest Variables: Generally manifest variables refer observable variables, which can be directly observed and have numerical responses like as gender or height. In structural equation modeling, latent variables are categorized often continuous and shown as rectangles on a route diagram.

Latent Variables: The latent variables refer that the variables which are not directly observable. These are represented as circles (ellipses) on a route diagram. It consists continuous curve and it has endless number of values.

Independent Variables: The external factors which are referred to be independent variables in SEM. Moreover, it is not receiving arrows in a route of the model, it means each variable are independent to each other.

Dependent Variables: An endogenous variable is known as dependent variable in structural equation modeling [SEM]. These variables are guided by arrows in a route model and dependent to each other. The figure of variables is given below.



Factor Analysis in Structural Equation Modeling [SEM]

A statistical technique is used in structural equation modeling [SEM] which to determine the linkage among the latent constructs that underline the observable data. Here we explore two different types of factor analysis: Explanatory and Confirmatory.

Exploratory Factor Analysis

A statistical approach is known as exploratory factor analysis [EFA] in structural equation modeling to find the underlying links between measured variables and latent constructs without forcing the results to fit the predetermined framework (Cudeck, 2000; Schreiber, 2021). Moreover, Exploratory Factor Analysis (EFA) comforts in identifying the quantity and type of latent factors that are responsible for the correlation patterns between the variables that are observed (Anderson, & Gerbing, 1988). Exploratory Factor Analysis supports researchers simplify large data sets by showing the dimensional structure of the data by identifying components based on eigenvalues and factor loadings (Tucker, & MacCallum, 1997). Factor extraction, rotation (using varimax or oblique rotation, for example), and interpretation are some of the processes in this method that are necessary to guarantee that the final factors are meaningful and statistically rigorous (Joreskog, 1993).

Exploratory Factor Analysis [EFA] is an crucial tool in the development and validation of theoretical frameworks within SEM as it is regularly active in the early phases of research to analyze and need to direct the creation of more confirmatory models (Fabrigar &

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Wegener, 2011). In this context, Thompson (2004) says that factor analysis's objectives are to ascertain the number of underlying effects that cause a field of variables, measure the degree to which each variable is linked to the factors, and learn more about the characteristics of the factors by identifying which factors effect performance on which variables (Pearl, 2012). Eigenvalues larger than unity are essential in Structural Equation Modelling (SEM) for evaluating the dimensionality as well as suitability of factor models, especially in the context of exploratory factor analysis (EFA). Moreover, in Exploratory Factor Analysis [EFA], a scree plot is a graphic representation that supports decide how many components are best kept for additional investigation. In addition, the eigenvalues of the given factors are exposed against the total number of factors in depending orders of the data. In this context, a scree plot often displays a steep descent which is followed by gradual leveling out much like a scree slope. Plotting level off (the "elbow") indicates how many elements to keep in mind since components beyond this point only slightly add to the explanation of data variation. Scree plot methods improve the reliability and interpretability of the exploratory factor analysis [EFA] outcomes by judging the collected data to take the decision-making process about the number of significant dimensions or components (Rahman et al., 2015).

Moreover, the dimensions or factors that the reason for additional disparity than a single observed variable generally observed as significant, according to the Kaiser Criterion, whether their eigenvalues are larger than one. This approach also supports in finding out how many dimensions or factors to keep in a model as components that have eigenvalues less than unity are often eradicated since it explains less discrepancy than a single variable (Ford et al.,1986).

Hence, the important underlying factors that are accountable for the significant numerical values of the overall variance are suggested by the existence of eigenvalues larger than unity, which also helps to accurate, validate and improve theoretical models in structural equation modeling[SEM]. In spite of, being commonly used, such criterion is commonly enhanced with other procedures like corresponding investigation and scree plots to provide a more reliable estimate of the factors or components in structure of the model.

Confirmatory Factor Analysis

A Confirmatory Factor Analysis [CFA] technique is used for testing a SEM model. In other words, a deeper conceptual model is recognized previously and then the data is composed to get in what way well the model fits or matches and attempting to "check" the researcher's theories on the interaction between constructs (Taherdoost et al., 2022).

Moreover, a statistical technique emphasize confirmatory factor analysis (CFA) is applied to determine if a proposed factor structure agrees with the data that have been observed (Asparouhov et al., 2018). Opposing to exploratory factor analysis [EFA], which begins with a particular model based on theory or previous research, CFA begins with a predetermined model in an effort to find probable underlying components (Khan et al., 2019).

Moreover, construction of measurement model for Confirmatory Factor Analysis [CFA] researchers need to indicate how many factors or dimensions there are and which observed variables are loaded into each separated component. It is ensuing, a number of goodness of fit indices are applied to assess for the model fitting, including the comparative fit index, chi-square test, and root mean square of error approximation [RMSEA]. Consequently, a good fit validates the established theoretical model and structures and their linkage by visualizing the proposed model properly describes the data.

Structural Equation Modeling [SEM] often employs strategies for confirmatory model validating and testing such as strictly confirmatory method and alternative confirmatory method and model development method (Collier, 2020; Joreskog, 1993).

Initial CFA Model Fit Indices

Model	NPAR	CMIN	DF	CMIN/DF	NFI	GFI	TLI	IFI	CFI	RMSEA
Threshold	-	-	-	5.00	0.90	0.90	0.90	0.90	0.90	0.600

Methods

A systematic document analysis method was used to perform on the use of structural equation modelling (SEM) in quantitative research. First, a thorough literature study is done to find pertinent publications, including conference papers and journal articles. To guarantee the inclusion of excellent research on relevant subjects, selection criteria are set. Then, important details such as research goals, theoretical underpinnings, study designs, SEM techniques, data gathering techniques, sample attributes, and primary conclusions are taken out of the chosen papers. Assessing the suitability of SEM for the research questions are addressed, the reliability of the statistical methods is applied, and the reliability of the measurement models are applied for components of the methodological review process.

Moreover, common themes, patterns, and trends are discovered by synthesizing study data, and then SEM's benefits, drawbacks, and contributions to the knowledge progress

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are critically examined. A total of 60 documents were initially identified, of which 40 met the inclusion criteria after an initial screening based on the relevance of the SEM methodology and quantitative approach. The analysis was concluded by ending with a summary of the most important discoveries and suggestions for new lines of inquiry. The types of variables (latent, observed) which were, SEM estimation techniques (e.g., Maximum Likelihood Estimation, Generalized Least Squares), fit indices (e.g., RMSEA, CFI, TLI, Chi-square), sample size considerations, path models, direct and indirect effects, and mediation/moderation analyses.

Results and Discussion

By breaking down the process into three stages: model setting, model assessment and change, and interpretation and reporting, the aspects that need to be taken into account when using SEM to analyze data. It is expected that the recommendations made would be taken into account by researchers as they work to enhance descriptive narratives and the quality of their study.

Furthermore, in Structural Equation Modeling (SEM) the fit indices GFI, CMIN/DF, CFI and RMSEA are commonly used to assess how well the offered perfect fits the experimental data. Consequently, the chi square statistics is divided by the degrees of freedom is also known as CMIN/DF [Chi-square/ Degree of Freedom]. It also modifies the Chi-square value which is based on the complexity of the model (DiLalla, 2000). A good match is often indicated by a CMIN/DF value of less than 2 (other sources suggest up to 3). The reported value of this ratio is 1.477. This result shows that the model and the provided data have a good match because it is much below the 2-point cutoff.

The estimated population covariance's share of variance is measured by the goodness of fit index of GFI, whose reported value is 0.861. Its ranges from 0 to 1, with values above 0.90 normally seen as suggestive of a good fit, however some studies accept values above 0.85 for complex models (DiLalla, 2000). It is near enough to be regarded as acceptable even though it is marginally below the conventional cutoff of 0.90, particularly for complex models (Cortina, 2020).

The CFI (Comparative Fit Index) evaluates how well the target model fits against a null, independent model. It similarly has a range of 0 to 1, with values above 0.90 denoting a good fit and values above 0.95 denoting an exceptional match (DiLalla, 2000; Ullman, & Bentler, 2012). Its reported value is 0.916, which also surpasses the 0.90 threshold and indicates a good fit.

The approximation error per degree of freedom is measured by Root Mean Square Error of Approximation [RMSEA], with lesser values demonstrating well fit (Ullman, & Bentler, 2012). A close fit is indicated by values less than 0.05, a decent fit is shown by standards between 0.05 and 0.08, and a poor fit is designated by values greater than 0.10 (DiLalla, 2000). The value reported is 0.048. Furthermore, as the result is below the 0.05 cutoff, it shows an excellent fit.

Analysis of Direct Effect in SEM

A direct effect in SEM can be described as the unmediated association between two variables. Mathematically, it is represented by the path coefficient between the independent variable (exogenous) and the dependent variable (endogenous). Consequently, the direct effects of the model are typically found by using standardized regression weights which reflects the strength of the connection or relationship between the variables, controlling for other variables in the appropriate model (Zhao et al., 2020).

For instance, in a simple structural equation modeling[SEM] model where variable X effects Y, the direct effect of variable X on variable Y is the path coefficient βXY which represents the influence of variable X on variable Y when no mediating variables are presented (Ullman & Bentler, 2012). Moreover, the direct impact affords a more forthright clarification of relations in SEM, as they signify the instant effect of one variable on another without connecting mediators (Kline, 2015). Finally, the direct effects are projected using statistical approaches such as Generalized Least Squares [GLS], Maximum Likelihood [ML] estimation.

Consequently, assessed pathway coefficients are tested for statistical significance to determine if the direct connection between independent and dependent variables meaningful. In addition, maximum likelihood estimation is usually applied to estimate direct effects, that providing standard errors and point estimates which are crucial for hypothesis testing (Hoyle, 2012). Similarly, the direct effects are known as same as to regression coefficients, thus positive path coefficients specifies that as the independent variable increases, then dependent variables also increase, remaining other variables constant. Nonetheless, a negative path coefficient advice an inverse relationship that the direct effect tells us how strong the connection is (Westland, 2015).

We can take an example if a direct impact between two variables X and Y is 0.35, it implies that a one unit rise in the variable X is associated with 0.35 unit growth in the variable in Y, assuming all other variables are remains at constant. Moreover, for the context of significance, the standardized path coefficients afford a measure of effect

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size, which is more useful for comparing the relative strength of different direct effects in the Structural Equation Modeling [SEM].

Moreover, in the context of uniform coefficients, the ranges between -1 and 1 with the value is closure 1 signifying stronger relationships. When we fit the model, the direct effects are more essential for understanding how variables are related in SEM. Moreover, the standardized coefficients give a technique to compare these effects across diverse paths inside the same model (Byrne, 2016). In the SEM model that include both indirect, mediating and direct effects, it is useful and important to distinguish between the two or more fully understand the association between variables. Indirect effects mainly happen when the independent variables effect a dependent variables over one or more mediators.

Finally, structural equation modeling [SEM] agrees investigators concurrently estimate direct and indirect effects which provide a comprehensive view of causal comparative structure. Furthermore, in direct effects, even when mediators are present which provide more critical insights into the whole mechanism of model outcomes (Zhao et al., 2020). Together with the direct effect is very essential for gaining the relationship between location area and students' performance, even though part of the relationship was facilitated by job satisfaction (Baron & Kenny, 1986; Hoyle, 2012).

SEM in Hypothesis Testing

First of all, we need to define the different types of variables. Only after defining, we need to compare them with the null and alternative hypotheses. For example, the independent variables are time of classroom practices, teacher's academic experiences, college regularity of the students, and well environment of the exam center. Similarly, the academic and achievement performance is dependent variable. We can assume there are two groups such as boys and girls, and we formulate the Null and Alternative hypotheses H0 and H1 respectively. Moreover, considering the testing whether coefficient alpha equals some a priori value $\alpha 0$. The Null and Alternative hypothesis are H0: $\alpha dif = 0$ and H1: $\alpha dif > 0$ where $\alpha dif = \alpha - \alpha 0$ and the sample is normally distributed.

Model fit estimation is also additional critical aspect of structural equation modeling [SEM]. For the determination of well hypothesized relationship and structures bring into line with the actual data. Structural equation modeling practices various appropriate indices like as Comparative Fit Index [CFI], Root Mean Square Error of Approximation [RMSEA], Tucker-Lewis Index [TLI], and chi-square test. The above given criteria guide to support assesses if the model adequately demonstrates the data. A proper model fit requires that the quantified associations which are likely truthful, while poor fit suggests that the model may need adjustment.

Advantages of Analyzing Direct Effects in SEM

Advantages of Structural Equation Modeling [SEM], directly it gives direct effects of more independent variables over the respective dependent variable. Structural equation modeling [SEM] offers a robust and very clear understanding of the immediate relations between latent and observed variables, free from the influences of intervening or controlling features (Moreira et al., 2016). Moreover, it [SEM] allows to the researcher to estimate direct and mediately accounting for measurement error and controlling for other variables, which increases the more accuracy of the results. Not only this, direct and mediating effect provide insight into the strength and direction of the relationships which serving clarification about the model pathways in the complex model (Nachtigall et al., 2003). Finally, structural equation modeling gives the flexibility for reducing the variables to make fit the model in diverse fields of the study. Through separating direct relationships SEM pays deeper understanding of how more specific variables influences the results even within complex systems of fixed factors.

Limitations of Analyzing Direct Effects in SEM

Despite the many advantages of the analyzing the direct and mediating effects of structural equation modeling [SEM] faces numerous limitations and challenges (Francis, 1988). One major issue is multicollinearity (Asparouhov et al., 2018; Bullock et al., 1994). The highly correlated independent variables can make it difficult to isolate the unique influence of each variable to the direct effect (Kline, 2015). Furthermore, the model misspecification is another significant challenge in structural equation modeling, which can also produce biased estimates leading to inaccurate conclusions (Davcik, 2014; Hoyle, 2012; Savalei & Bentler, 2006). Structural equation modeling needs large sample sizes to ensure reliable results, which may not always be feasible. Additionally, developing and testing mediating models can be time-consuming, requiring careful design and validation. Notwithstanding these challenges, SEM remains a valuable method for uncovering and understanding mediating effects in research.

Model misspecification is another challenge, as incorrect or incomplete models can produce biased estimates, leading to inaccurate conclusions about direct effects (Byrne, 2016). Additionally, sample size requirements in SEM are often large, especially in complex models, to ensure reliable and stable estimates of direct effects (Schumacker & Lomax, 2016). Overfitting, which occurs when the model fits the sample data too closely, can also distort the interpretation of direct effects in new datasets (Hoyle,

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2012). These challenges necessitate careful model building, validation, and sample size considerations to confirm the correctness and generalizability of findings.

Analysis of Mediating Effect in SEM

In Structural Equation Modeling [SEM], the analysis of mediating effects plays crucial role in understanding the indirect relationships between variables. A mediating effect occurs when different independent variables influence respective dependent variable through one or more dominant variables is known as mediators. Moreover, structural equation modeling is particularly well suited for the analyzing the complex causal comparative pathway as it shows investigators to estimate both indirect and direct effect providing a more comprehensive opinion of the relationships within a model(Hair et al., 2019; Taherdoost et al., 2022). Moreover, mediating effects also referred to as indirect effects, are the mechanisms over the independent variables exerts its effect on respective dependent variables.

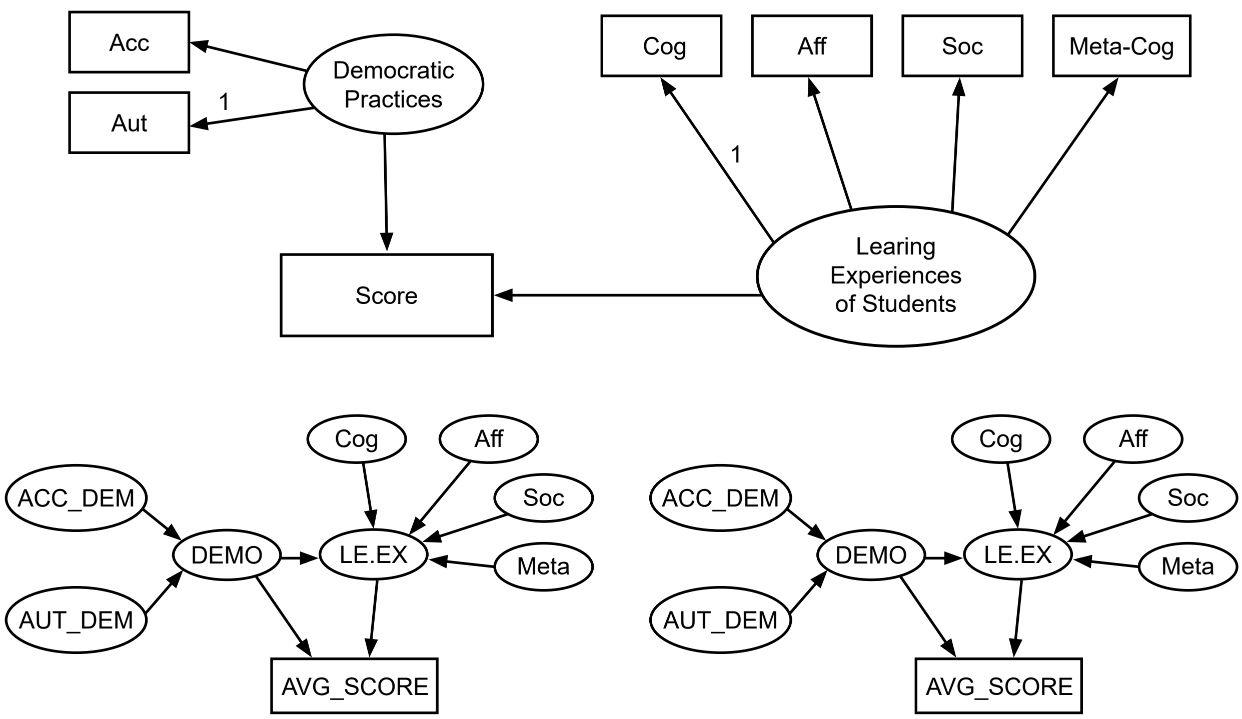
Once the independent variables affect the dependent variables only through mediator, this is referred to as a full mediation. In contrast, partial intervention occurs when the independent variables have both a direct effect on the respective dependent variable and an indirect effect through mediators (Hair et al., 2019). Moreover, Preacher and Hayes (2004) emphasize that SEM-based mediation models, unlike traditional regression methods, allow for multiple mediators (Baron & Kenny, 1986), and complex relationships, providing more nuanced results. SEM can also handle measurement errors through latent variables, improving the accuracy of mediation analysis (Schumacker & Lomax, 2016).

Additionally, SEM allows for the combination of latent variables, emphasizing for finding errors and offering a more vigorous breakdown of hypothetical constructs (Kline, 2015). The ability to model multifaceted systems of relationships, including multiple mediators or moderators, makes structural equation modeling a extremely comprehensive and flexible tool (Byrne, 2016; Lei, & Wu, 2007). However, SEM also has drawbacks. Moreover, its complexity requires a deep understanding of statistical theory and software, making it challenging for novice researchers (Nachtigall et al., 2003). Mainly, large sample sizes are often needed to obtain reliable results, and condition of models can lead to erroneous conclusions (Schumacker & Lomax, 2016). Additionally, while SEM suggests causal pathways, it cannot ultimately found connection, particularly when based on cross-sectional data (Hoyle, 2012). Despite these few boundaries, structural equation modeling remains a commanding technique for analyzing mediating effects and exploring intricate relationships within data.

Examples of SEM

Mathematics teachers' accountability with six dimensions (accountability to students, school, profession, parents, community and government), mathematics teachers autonomy (autonomy to curriculum, pedagogy, assessment, governance, socio- cultural and moral and ethical), and students' learning experiences (cognitive, affective, socio-cultural and metacognitive) are all considered as independent variables while mathematics achievement scores is dependent variable. The structural equation modeling model assesses the new model how teachers' Accountability (Acc) and Autonomy (Aut) form the latent variable Democratic Practices, which influences students' achievement scores both indirectly and directly.

The indirect effect occurs through the mediating variable Learning Experiences of Students, composed of Cognitive (Cog), Affective (Aff), Socio-cultural (Soc), and Metacognitive (Meta-Cog) dimensions. Democratic Practices directly enhance achievement and also improve students' learning experiences, which in turn boost achievement. Single-headed arrows represent causal paths, and fixed loadings (1) ensure model identification. If the direct effect weakens but remains substantial after counting the mediator, partial mediation is designated; if it becomes non-significant, full mediation is achieved. The model thus tests both direct and mediating effects of democratic practices on student achievement, which are given following figure.



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Conclusion

In structural equation modeling, direct effects represent immediate, visible, and unmediated relationships between variables. Such visible models are fundamentally easier to understand than causal structures. By estimating direct effects, researchers can quantify the strength and significance of relationships, which provides insight into how independent variables directly influence outcomes. The researcher's simultaneous estimation of direct, indirect, and total effects provides a powerful way to explore complex theories and uncover hidden causal pathways. However, direct effects analysis must be used with caution, as issues such as multicollinearity, model specificity, and sample size limitations can affect the accuracy of the results. When applied correctly, direct effects analysis using structural equation modeling can be an invaluable tool in quantitative research, facilitating a deeper understanding of causal mechanisms across a wide range of subjects.

Similarly, in structural equation modeling, researchers can gain valuable insight into the instruments by which variables influence each other by analyzing the mediation effects alone. Structural equation modeling's ability to estimate direct and indirect effects simultaneously, account for measurement error, and include latent variables makes it an ideal tool for mediation analysis. However, the complexity of mediation models and the need for large sample sizes pose challenges that researchers must carefully explore. Despite these challenges, researchers have found that using SEM to analyze mediation effects has significantly advanced the understanding of causal relationships in a wide range of fields. Each index falls within acceptable ranges according to established criteria, indicating that confirmatory factor analysis and structural models are robust and valid.

Implication

This is the era of 21st skills. Many researchers are conducting quantitative research by taking large samples size. In this context, Structural Equation Modeling [SEM] is also used to find out direct and mediating effects among the variables to variables (independent and dependent). Structural equation modeling suggests promising opportunities for advancing research in diverse fields such as education, psychology, and business by allowing the exploration of complex relationships. The researchers may use it in preparing curriculum, applying pedagogy and assessment procedure as well as feedback system. It also helps future studies for enhancing models to capture dynamic and long-term changes through longitudinal research study over time.

By applying this model, the quantitative researchers may address the issues and misconception of measurement errors by refining fit indices. Moreover, this model has become very important in order to accurately determine the relationship between as various variables socio-cultural and economic affected to each other's factors affect research in the current era.

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