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Research paper

Addressing The Issues of Low Degrees of Freedom and Associated Poor Validation Estimates of Science Education Models: An Advocacy for The Application of Confirmatory Network Analysis

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Abstract

Generally, science education models have a low degree of freedom df, and this psychometric aspect negatively impacts the overall goodness of fit estimates obtained on conducting CB-SEM-based Confirmatory Factor Analysis (CFA) on the hypothesized latent models using the Maximum Likelihood (ML) estimator. To address this issue, the state-of-the-art Confirmatory Network Analysis (CNA) approach is advocated, which uses the adjacency matrix in estimation and treats the data type of the data collected using survey questionnaires as ordinal using the appropriate Diagonally Weighted Least Squares (DWLS) estimator to provide the proper scaled goodness of fit estimates of the network. In the present study, the goodness of fit estimates of a science education model involving the perception of 918 secondary school students of India on their science constructivist learning environment, epistemological beliefs in science, science self-efficacy, science academic flow, and science academic achievement were found from the traditional latent variable modeling and the latest network perspectives. Data analysis was conducted using SPSS AMOS Ver 23.0, several packages of R and through generated using ChatGPT Ver. 5. The scaled goodness of fit estimates of confirmatory network analysis produced a better picture of the reality over confirmatory factor analysis, and provided deeper insights on the interactions among the studied variables as were graphically established by the differences in the Bland-Altman plots of the CFI, TLI, RMSEA and SRMR estimates of the two approaches. Educational and psychometric implications of the study are discussed.

Keywords: *Bland-Altman Plots; Confirmatory Network Analysis; Confirmatory Factor Analysis; Degree of Freedom; Science Education Models.*

1. Introduction

Science education plays a significant role in the development of problem-solving skills, critical thinking, and creativity among adolescents at the secondary school level, which cast their ramifications on the development of society, its economic progress, while observing the essence of sustainable development goals [8]. The goal of science education is to be instrumental in developing adolescents into adults who can creatively and scientifically solve the issues of the societies in which they will dwell in the future [43]. For meeting this mandate, the field must be supported by research-driven findings, which come under the purview of science education research. It tries to gain insights into the ways in which the subject of science can be learned by the students and taught optimally by the teachers. Its approach is multi-disciplinary and grounded in other fields like educational psychology, statistics, and data science.

Researchers in the field of science education research most often try to test the relationships among multiple science education-related traits in the sample subjects by proposing hypothesized models driven by theory and involving representation of the traits as operationally measurable variables, to statistically substantiate the proposed models with empirical data [34]. The statistical approach found to be most appropriate for this purpose is called the Structural equation modeling [32]. A special case of structural equation modeling called the Confirmatory factor analysis (CFA) forms the statistical technique, which is applied on the obtained data to test the validity of any proposed theory based model using several statistical software and formulae or estimators [11], most prominent and quite developed of whom is the covariance-based SEM (CB-SEM) via maximum likelihood estimator [31],[33],[28] using software like SPSS AMOS [3].

To perform the covariance-based structural equation modeling (CB-SEM), a researcher gathers the data of each of the variables (p) whose relationships are to be studied. In the first stage of the CB-SEM approach, called model specification, the software used to carry out the statistical analysis is specified, including the number of variables involved in the model, their status as being the predictor or the predicted, and relationships existing among them, as guided by a theory, graphically, which form the path diagram of the model. In the second stage, called the model identification, the data file containing the empirical data collected from the sample subjects of the study is attached to the software. The software then uses the provided data to generate the sample-based variance-covariance matrix and model-implied variance-covariance matrix. The latter matrix has p variances in the predictor variable as its diagonal and p (p-1)/2 covariances in the rest of the dependent variables as its off-diagonal elements. Then, the latter matrix's unique elements or useful information are selected, technically called the distinct sample moments or data points (mathematically represented as p (p+1)/2). The estimation of the unknowns in the model, using the provided data, involves finding certain elements associated the path diagram, namely, the factor loading, variance, covariance, residual, regression path, which are technically called the free parameters. Certain elements which are manually made constant and allowed to change in the path diagram (for example, fixing one of the factor loadings to 1 to set the scale of the latent variables), technically called the fixed parameters. The difference between the available useful information for calculating the unknowns (data points, p (p+1)/2) and the unknowns themselves (free parameters) is called the degree of freedom df of the model. For the model to be estimated and later tested, it is critical, that the number of available useful information from the data or data points p (p+1)/2 be greater than the number of unknowns or free parameters, or df >0 [57]. In the third stage, called the model estimation, the software finds the values of the free parameters forming the model-implied variance-covariance matrix and the obtained data based sample variance-covariance matrix. Then, using the estimators like Maximum Likelihood (ML), parameters which measure how these two matrices are close to each other are computed. In the fourth and final stage, called model evaluation, how well the matching between these two matrices took place is found out and expressed statistically using estimands like Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Residual (SRMR) [29].

However, most of the psychological models studied in science education have a lower degree of freedom [56]. This inherent issue of low degree of freedom associated with the science education models impacts the validation results of these models carried out using the popular Maximum Likelihood (ML) estimator-based CB-SEM approach, and is manifested in the form of low TLI and high RMSEA values even for good models since these estimands are dependent on the degree of freedom df [52]. Also, the data type of the survey questionnaire-based data is ordinal in nature and requires estimators that make use of matrices based on polychoric correlations (the statistical technique that measures the relationship between ordinal categorical variables), like the unweighted least squares (ULS) and diagonally weighted least squares (DWLS) [62]. Since the degree of freedom df is a function of the observed variables or p, increasing the number of variables in the study can quadratically increase the degree of freedom of the model. A rise in the number of studied variables inevitably leads to the collection of more data. The collected data always contains two parts, namely the signal and the noise [59]. While the signal is the useful part of the data, the noise is the total of all possible sources of error associated with the collection of the data. Increasing the complexity of the model by raising the studied variables p can have certain impacts on the agreement of the empirical data with the proposed model [53]. If the signal part of the data is more, the model and data fit very well (since the degree of freedom df is high here and hence high goodness of fit), indicating internal validity and generalization of the findings of the model in other contexts or the confirmation of external validity of the model. If the signal part is less in the data, the model might not be possible to estimate at all, a condition technically called the underfitting. However, if the collected data has more noise part than the signal, still, there will be an agreement in the empirical data and the model (high goodness of fit/internal validity), but the findings of such a model cannot hold in another context or would lack generalization of external validity, a scenario technically called model overfitting. Increasing the complexity also increases the tendency of the model to overfit with data, beating the very purpose of conducting quantitative research [47].

Also, according to the concept of falsifiability proposed by [49], the validity of any scientific theory is related to its probability of being proven to be wrong through empirical data. While conclusive affirmation of a hypothesis is not possible, it is quite possible to conclusively refute a hypothesis. On the contrary, the hallmark of unscientific claims is that they are mostly right or cannot be falsified easily. In the case of perfectly fitting or overfitting models as discussed above, the degree of freedom (df) is either low or zero, and hence these models have a low degree of falsifiability since the available data can be fit with any theory. Such a scenario dangerously gives an impression of the studied models being almost and always right. This is why prior studies failed to address low df related issues, especially in the context of science education models.

As part of recent developments taking place in the field of Network Psychometrics [18], [14] reported the validity of structural equation modeling fit indices to be largely applicable on confirmatory network analysis [17]. This method recognizes the fact that the type of the data collected using survey questionnaires is ordinal, and hence estimation of the variance-covariance matrix requires polychoric correlation based diagonally weighted least squares (DWLS) estimator. The factor loading estimates obtained from DWLS estimator are more accurate in comparison to ML estimator for the categorical ordinal data of survey questionnaires [41], [45]. Also, there is no dependency of the estimates of model fitting on degree of freedom df in Confirmatory network analysis. Here, estimation of the network structure's fit with the empirical data is made feasible using adjacency matrix. This matrix defines which edges of the network to be constrained to zero and which are to be ultimately estimated. Out of the large number of possible network models generated owing to large number of permutations and combinations of the edges, network analysis uses regularization techniques like Extended Bayesian Information Criterion glasso or EBICglasso to arrive at the robust and simplest possible network [17]. Moreover, interrelationships among the studied variables as represented graphically in Network Psychometrics, are way more realistic in nature, existing in the form of an ecosystem like network, based on mutualism or reciprocal causal interactions perspective, instead of the simplistic, reflective and latent structural linear models [54], [58]. Mutualism models treat psychological phenomenon to be consisting of observables or manifest variables which reciprocally and dynamically influence each other emerging as a causally connected system or network [5]. The studied variables are represented in the network as circles called nodes, and the relationship between the nodes is represented as line edges, which are partial correlations between the two nodes after controlling for the influence of all other nodes of the network on them [18]. More importantly, [10] reported the equivalence of latent variable modeling-based factor loadings and the network models-based network loadings, carrying forward the earlier works of [22], [30], [44], and [60]. In the context of structural equation modeling, model parameters like factor loadings are the measure of how an item measures its latent dimensions and construct in measurement models and how strongly it is influenced by other latent variables in a structural model [15]. But, in the context of network psychometrics, the variables are autonomous and come together to form the factors/dimensions rather than being mere reflections of the latent factors [12]. As a result, a network loading represents a measure of a node's (a variable's) unique contribution in the formation of a latent factor [9].

The present study tried to address the low degree of freedom related issue of science education models and its associated poor results by validating a structural model involving certain important and related science education variables like Constructivist Learning Environment, Epistemological Beliefs in Science, Science Self-Efficacy, Science Flow and Science Academic Achievement among secondary school students, first using CB-SEM confirmatory factor analysis (CFA), and then compared the results of this statistical analysis with the results obtained by validating the network model of these variables using confirmatory network analysis (CNA). Like the structural equation modeling approach (Kline, 2015), the latter approach also primarily involves comparison of two variance-covariance matrices, namely the variance–covariance matrix implied by the network versus the variance–covariance matrix that was observed in the sample [36].

2. Method

2.1. Population

The population of the present study comprised secondary school students belonging to the 9th and 10th classes of the CBSE board and of an average age of 14.5 years from the state of Andhra Pradesh, India. The rationale behind the selection of these students from the mentioned class levels is that they are eligible to appear for the Program for the International Student Assessment (PISA) test, which measures the academic performance of adolescents in science at international levels.

2.2. Sample and procedure of data collection

The sample of the study comprised 918 secondary school students, selected through a stratified random sampling technique from one school each from all eight districts of the state of Andhra Pradesh. There were 400 girls (43.57%) and 518 boys (56.42%). Similarly, there were 520 students (56.64%) from the 9th class and 398 students (43.35%) from the 10th class. The researcher personally visited the schools of the region and explained the purpose of the visit to the students. The head of the institution and the teacher in the class helped the researcher in the collection of the data during regular classroom sessions. All students voluntarily participated in the study after being assured of the purpose of the data collection and the anonymity of the data. The average age of the subjects was 14.5 years. The physical copies of the questionnaire were finally distributed to the subjects, and they returned the filled forms in 40 to 45 minutes. The study was approved by the Institutional Ethics Committee (IEC) of Lovely Professional University, India, bearing the registration number EC/NEW/INST/2022/3110.

2.3. Instruments

The Constructivist learning environment survey in Science class (CLES) developed by [46] was chosen to measure the perception of secondary school students regarding their perception of science class is constructivist in nature or not. Their epistemological beliefs about the subject were measured using the Epistemological Beliefs in Science Scale developed by [13]. Science self-efficacy was measured using the scale developed by [23]. The Academic Flow scale developed by [25] was used to develop the science academic flow scale by the researchers. Science academic achievement was measured using the cumulative grade point average (CGPA) of the students. Network psychometrics was used to validate and purify all the foreign origin scales in the Indian context, and acceptable to robust results were obtained for them.

2.4. Statistical analysis

The covariance-based structural equation modeling CB-SEM confirmatory factor analysis was carried out using SPSS AMOS [4] Ver. 23.0. The network psychometrics-based confirmatory network analysis was carried out using the lavaan [51] package of R(2020), and codes generated using ChatGPT Ver 5 produced the plot of confirmatory network analysis based on the adjacency matrix. The package qgraph [20] was used to estimate the node predictability plot and the network loadings. Superiority of the confirmatory network analysis (CNA) over the traditional confirmatory factor analysis was shown graphically using the Bland-Altman Plot, whose R codes were generated using ChatGPT Ver 5 and R packages like bootnet [18], ggplot2 [61], patchwork [48], and BlandAltmanLeh [42].

3. Results

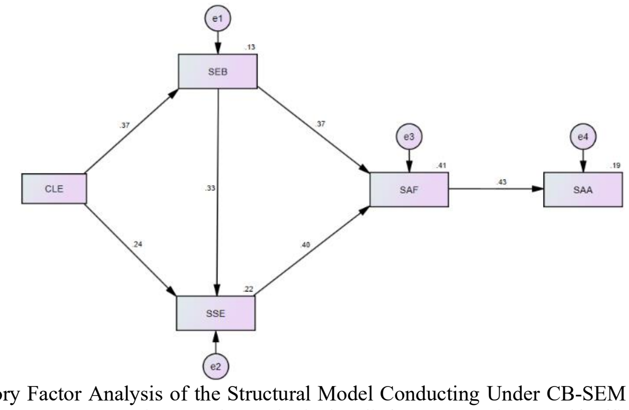

Fig 1: Path Diagram of the Confirmatory Factor Analysis of the Structural Model Conducting Under CB-SEM Using SPSS AMOS Ver. 23.0 Software; CLE = Constructivist Learning Environment, SEB = Science Epistemological Beliefs, SSE = Science Self Efficacy, SAF = Science Academic Flow and SAA = Science Academic Achievement

Table 1: Goodness of Fit Estimation Based on Factor Loadings

S. No.	Estimate for df=4.0	Benchmark of the Estimand	Standard ML-based Estimate	Remark on Goodness of Fit
1	CFI	0.95	0.951	Excellent
2	TLI	0.95	0.878	Not Acceptable
3	RMSEA	0.05	0.120	Not Acceptable
4	SRMR	0.08	0.0621	Good

In the Confirmatory factor analysis conducted for the displayed model, the number of distinct sample moments data points or available useful information was 15. The number of distinct parameters to be estimated or the unknowns was 11. As a result, the degree of freedom df = 4, which made the model over-identified. Hence, estimation was possible. The factor loadings obtained were 0.37 (between CLE and SEB), 0.24 (between CLE and SSE), 0.37 (between SEB and SAF), 0.40 (between SSE and SAF), and 0.43 (between SAF and SAA). All these regression weights were highly significant. The goodness of fit estimates of the model, when the data were assumed to be of continuous interval data type and under the most used maximum likelihood (ML) estimator, were excellent for CFI=0.951, not acceptable for TFI=0.878, not acceptable for RMSEA=0.120, and good for SRMR=0.0621. Obtaining such unacceptable values of TLI and RMSEA is common when the degree of freedom df is as low = 4 [62], especially for science education models. Also, both TLI and RMSEA are sensitive to model complexity [21].

To address the above discussed shortcomings in the proposed model, network psychometrics based confirmatory network analysis was conducted on a network where the nodes were the studied variables CLE = Constructivist Learning Environment, SEB = Science Epistemological Beliefs, SSE = Science Self Efficacy, SAF = Science Academic Flow and SAA = Science Academic Achievement, and edges were the partial correlations between two nodes blocking the influence of the rest of the nodes of the network on them. The following plot and estimates were obtained

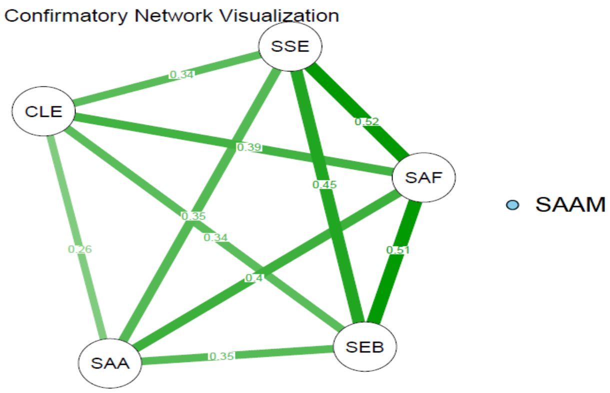

Fig. 2: Plot of the Confirmatory Network Analysis (CNA) of Science Academic Achievement Model (SAAM); Here, the Nodes Are CLE = Constructivist Learning Environment, SEB = Science Epistemological Beliefs, SSE = Science Self-Efficacy, SAF = Science Academic Flow, and SAA = Science Academic Achievement. the Edges Are Represented as Green Lines with Network Loadings Mentioned on Them. The Broader and Darker the Lines, the Stronger the Relationship Between the Nodes.

Table 2: Goodness of Fit Estimation of the Network Obtained Using DWLS Estimator

S. No.	Estimand	Strict Benchmark of the Estimand	Standard DWLS-based Estimate	Remark on Goodness of Fit
1	CFI	0.95	0.993	Excellent
2	TLI	0.95	0.986	Excellent
3	Scaled CFI	0.95	0.985	Excellent
4	Scaled TFI	0.95	0.969	Excellent
5	RMSEA	0.05	0.072	Good
6	Scaled RMSEA	0.05	0.097	Not acceptable
7	SRMR	0.08	0.032	Excellent
8	Scaled SRMR	0.08	0.032	Excellent

The confirmatory network plot showed the network formed by the studied variables and the strength of the relationships between them through the estimated network loadings. Constructivist learning environment in science classroom was found to be strongly related to science academic flow (0.39), followed by epistemological beliefs (0.35) and self-efficacy (0.34) in science subject. Its relationship with academic achievement in science was the least (0.26) in the network. The relationship of epistemological beliefs with experience of flow in the science classroom is the strongest (0.51), followed by its relationship with self-efficacy (0.45) and academic achievement in science (0.35). Science self-efficacy is strongly related to academic flow (0.52) and less strongly related to science academic achievement (0.35) in the network. A considerable improvement in the goodness of fit estimates was seen when the diagonally weighted least squares (DWLS) estimator based on confirmatory network analysis was conducted on the data using the lavaan package of R, conducted on RStudio. The diagonally weighted least squares (DWLS) estimator is a statistical technique that can provide better goodness-of-fit estimates while comparing the hypothesized network with empirical data, especially when the latter is obtained from questionnaires and is ordinal in its type. Apart from the standard estimands, their most accurate and recommended scaled versions were also obtained. CFI, TLI, and SRMR estimates in their scaled version (0.985, 0.969, and 0.032, respectively) showed excellent goodness of fit, although there was room for scaled RMSEA (0.097) to improve. Overall, the estimates indicated the robustness and stability of the obtained network.

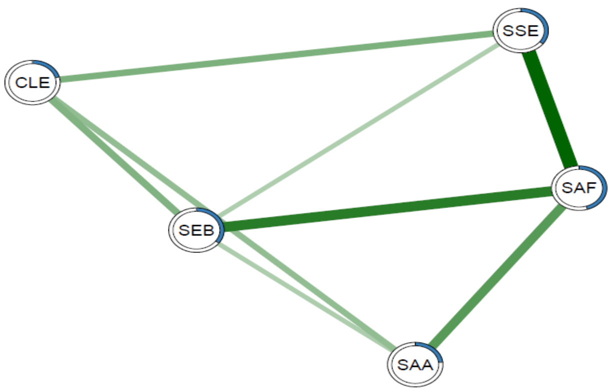

Fig. 3: Node Predictability Plot; Here the Nodes Are CLE = Constructivist Learning Environment, SEB = Science Epistemological Beliefs, SSE = Science Self-Efficacy, SAF = Science Academic Flow, and SAA = Science Academic Achievement. the Edges Are Represented as Green Lines. The Broader and Darker the Lines, the Stronger the Predictability of A Node by the Rest of the Network.

Table 3: Node Predictability R^2

S. No.	Node	R^2
1	CLE	0.210
2	SEB	0.349
3	SSE	0.352
4	SAF	0.452
5	SAA	0.233

Since in the context of network psychometrics, network loadings refer to the measure of node predictability [27] in the network, the estimated R^2 was estimated for each of the nodes in the network. The node science academic flow was the most strongly predicted element of the network, and the node constructivist learning environment was a weakly predicted member of the network. The science self-efficacy node established its critical role by being the second most predicted node in the network. Very closely associated with self-efficacy is the node of epistemological beliefs in science predicted by the entire network. The most important node with respect to science education research and policy formulations, namely, science academic achievement, was one of the weakly predicted nodes in the network.

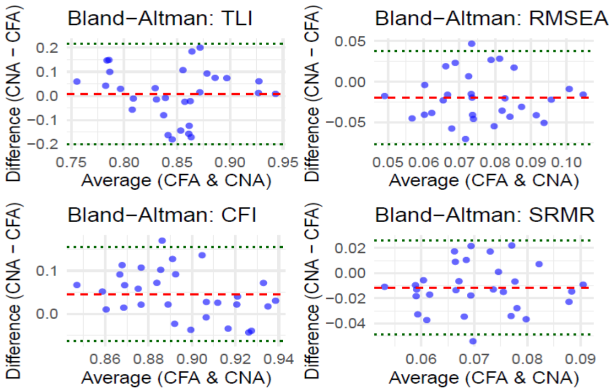

Fig. 4: Bland Altman Plot of the Difference between Confirmatory Network Analysis (CNA) and Confirmatory Factor Analysis (CFA) Approaches with Respect to Their Goodness of Fit Estimates CFI, TLI, RMSEA, and SRMR

The Bland Altman Plot [1], [24] is a statistical technique to measure the agreement between two measurement methods such that their values are sufficiently close enough to be used interchangeably. Here, these plots were generated to see whether the estimates of goodness of fit obtained using CNA and CFA can be too similar in agreement that they can be interchanged or not. The plots on the x-axis show the average of the CNA and CFA methods, and the difference of these methods with respect to their CFI, TLI, RMSEA, and SRMR estimates along the y-axis. The red mean difference line represents any systematic shift between estimation methods, while the two dotted 95% limits of agreement (mean difference ± 1.96 SD) capture the expected range within which most differences lie. If most of the blue dots are close to the red horizontal line, then the dotted lines of limits of agreement would also be narrow, suggesting strong consistency in the two methods. Higher differences shown through the wider spread of the blue dots and limits of agreement imply estimation choice between CNA and CFA may affect the interpretation of model fit. From the above obtained plot, it is evident that the limits of agreement of the difference is narrow for SRMR estimate for the two approaches. However, there are relatively wider limits of agreement of differences between CNA and CFA approaches with respect to their estimates of CFI, TLI, and RMSEA. These plots indicate the superiority of Confirmatory Network Analysis (CNA) over Confirmatory Factor Analysis (CFA) for validating psychological models.

4. Discussion

A large number of psychological models in science education study the interaction between variables measuring the cognitive, emotional, and motivational traits in the students using path analysis. As a result, these models have relatively fewer data points left to test the models after estimating them, owing to the large number of unknown parameters to calculate. This aspect leads to a fall in the degree of freedom of these models [56]. Low degrees of freedom produce unacceptable estimates of TLI and RMSEA estimated using the maximum likelihood estimator of the Confirmatory factor analysis technique, even for relatively good models, and create a case of false negatives. This issue was addressed in this study by proposing the usage of Confirmatory network analysis as a viable alternative for validating psychological models using the ordinal data type based on diagonally weighted least squares (DWLS) estimator. The latter approach provided better estimates of model validation since its estimates are dependent on the adjacency matrix instead of degrees of freedom df. The superiority of this approach over confirmatory factor analysis was shown using the wider differences in the Bland Altman plots of the estimates of the two approaches. Also, confirmatory network analysis (CNA) will allow the generalization of the findings obtained from a cross-sectional local setting to multiple educational and cultural settings across countries [40]. Like confirmatory factor analysis CFA, this technique can also allow usage of 70% of the collected data for exploratory purposes and 30% of the remaining data for proving the hypothesized relationships among the variables [7], [39].

Analysis of the network architecture provided valuable insights, like the science academic flow being the most important variable to be promoted in the science classroom by teachers at the secondary school level. The very close interaction of this variable with the very critical trait of self-efficacy in science implies that these two traits feed on each other [33]. Both these variables of belief in studying science and experiencing a sense of flow during this activity are related to the development of students' own beliefs on the nature of science subject or epistemological beliefs [55]. The intricate relationships of these variables with the constructivist learning environment of a science classroom indicate the importance of teaching science using the 5E approach [6] of Engage, Explore, Explain, Elaborate, and Evaluation. Ultimately, such endeavors by the teachers and the students can bear fruit by improving the academic achievements of the students in science in the board exams [38], [2], [26]. The findings of this study hence hold importance owing to the importance of raising the performance of secondary school students in science subjects in general for producing a quality STEM workforce for the country in the future [37]. All the study variables come together as the autonomous elements to collectively form a psychological phenomenon of science academic achievement, graphically represented as a network, with robust goodness-of-fit psychometrics.

Although the obtained results through network psychometrics seem to be encouraging, it is worth remembering that the traditional approach of confirmatory factor analysis is deeply rooted and studied in the literature. In contrast, the field of network psychometrics and its statistical techniques, like confirmatory network analysis, are evolving and mainly make use of the bootstrapping technique. Its body of literature is less in comparison to the work available on structural equation modeling-based confirmatory factor analysis. Also, although [14] reported Conventional SEM cutoffs to be largely generalizable to CNA, there is a lack of theory construction for network analysis, and the stricter cutoff values of 0.03-0.04 for RMSEA and 0.96-0.97 for CFI and TLI as recommended by this study were based on synthetic networks-based simulations alone. While the estimates of scaled CFI and scaled TLI in this study meet such new cut-offs, the values of scaled RMSEA are higher than their respective fresh benchmarks. Future studies can involve replication of the network architecture of science academic achievement in pristine contexts and populations. However, such developments can be possible only when the researchers and the practitioners (school teachers) are adequately trained on the usage of the free R package of “psychonetrics” [17] to apply confirmatory network analysis to effectively verify and validate science models using the open-source RStudio.

5. Conclusion

The present study tried to address a critical issue of obtaining unacceptable goodness-of-fit indices even for relatively valid psychological models with a low degree of freedom df. Confirmatory network analysis (CNA) as an alternative to the traditional approach of Confirmatory factor analysis (CFA) is proposed in this study to be adopted to validate theory-driven models, especially in science education. It is hoped that the practitioners and research scholars can take cognizance of the findings of this study and remain persistent in studying their hypothesized models using the new approach further, instead of abandoning them on obtaining results using the traditional approach of model validation.

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The authors did not receive any funding for this study.

Conflict of Interest Disclosure

The authors have no conflict of interest to declare.

Ethical Approval

The Institutional Ethics Committee (IEC) of Lovely Professional University approved the work through its reference number EC/NEW/INST/2022/3110.

Informed Consent Statement

Informed consent was obtained from all subjects involved in the study.

Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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