Validation of Science Self-Efficacy Scale in the Indian Secondary School Students using Network Approach

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Abstract:

The Science Motivation Questionnaire – II developed by Glynn and Koballa (2006) for college students was used to validate the science self-efficacy items in it through network approach. 110 Indian secondary school students (49 boys and 61 girls) were the sample subjects of the present study. Owing to the ordinal type of the data obtained from this tool, it was validated using the fresh approach. Exploratory graph analysis (EGA) through *Glasso* technique revealed single cluster, confirmed further through structural consistency coefficient of 0.744 and goodness of fit estimates of the network, CFI.robust = 0.954, TLI.robust = 0.908, RMSEA.robust = 0.086 and SRMR_Bentler = 0.047, found using *WLSMV* based Ordinal confirmatory factor analysis. Regularized network, centrality indices, edge-weight accuracy confidence plot, correlation stability plot, edge difference plot, node difference plot and node predictability plot were also generated. The CS-coefficient of the network was obtained poor at 0.126 due to the less sample size of the study although. All these plots were generated using *EGAnet*, *qgraph*, *bootnet*, *psychtools* and *mgm* packages of RStudio openware. Node predictability coefficient R^2 of the nodes 4 and 5 was the highest at 28.5% and 28.4 % respectively. Educational implications of the study on science education and its research are discussed.

Keywords: Science Self-Efficacy, Network Approach, Science Self-Efficacy Validation, Science Education, Secondary School Students

Introduction:

Availability of STEM (Science, Technology, Education and Mathematics) graduates is considered to be a rich human capital, instrumental in bringing prosperity to the concerned nation (Podobnik et al., 2020). However, the interest of the students towards this field has been declining (Thomas and Watters, 2015), evident through the lesser enrolment rate of them in its courses in recent times (Khan et al., 2023; Obi and Obi, 2019). One of the identified factors responsible for this serious state of STEM education and science education in particular is the low science efficacy in these students (Blotnicky et al, 2018). It is pertinent to mention here that while mathematics is the language of science, engineering uses the knowledge of both science and mathematics for the betterment of mankind and technology emerges as the very study of such a human created and controlled world (Dugger, 1993). It implies that science education lies at the very epicentre of STEM education.

The origin of science self-efficacy as a construct emerges from the self-efficacy works as per the Social cognitive theory proposed by Bandura (1986, 1982, 1977) and hence is conceptualized as "the student's perceptions of his or her competence in science tasks" (Hu, Jiang and Bi, 2022). Most of the studies on this variable took place for the population of college students (Ainscough et al., 2016). However, the measurement of this trait in high school students, in particular is essential, because it is during adolescence that this trait get solidified in the personality although continues to develop over an individual's lifetime (Bandura, 1994). This stage of development also marks the presence of this trait at the lowest level in these students (Eccles et al, 1997). Also, the structure of education system across the world is such that after the completion of high school, students prepare themselves for the transition to tertiary education where they are expected to display academic autonomy. Lack of self-efficacy in science in the stage prior to college and university education can make these students drop out from science and science related STEM programs, further reducing this trait in them (Larose et al., 2006). Also, those students high in this trait at school level were found to pursue STEM education in later years (Byars-Winston et al., 2010). Hence, high school is a very critical period for the cultivation of science self-efficacy in the students (Hu, Jiang and Bi, 2022).

The research on self-efficacy variable is conducted in an integrative manner, instead of a stand-alone mode, with self-efficacy being the central variable among a host of other highly related and relevant variables of STEM education (Digna and Carme, 2019). In this context, the length of the tool measuring self-efficacy plays an important role, and the investigator needs to appreciate the trade-off existing between the extent of variance of the construct captured through its coverage in the tool and the tool's parsimony. For practical purposes, it is required that shorter measures of self-efficacy be tested for their psychometric robustness using new approaches like network psychometrics and also for their cross-cultural ecological effectiveness so that the research community across the board can get benefited. Hence the present study, which aims to validate the five items self-efficacy sub-scale originally developed by Glynn and Koballa (2006) as part of the Science Motivation Questionnaire – II for college students, and extend its usage to a fresh population of high school students in India using the network approach.

Methodology:

Participants:

110 students (49 boys and 61 girls) from a school under Regional Institute of Education campus, Bhubaneshwar, Odisha, India, affiliated to the Central Board of Secondary Education, voluntarily participated in the study. All the students received instructions in English throughout their academic life and were fluent in the language. The investigator sought and obtained formal permission from the institution to gather data for her research work having personally visited it. The entire work also received its approval from the Institutional ethics committee, Lovely Professional University, Phagwara, India, bearing reference number LPU/IEC-LPU/2024/2/34

Instrument:

Measuring Science Self-Efficacy:

The present questionnaire was developed by Glynn and Koballa (2006) as a tool to measure motivation among college students to learn science and relationship of motivation to other related characteristics. Self-efficacy is one such related variables included in this questionnaire and it is defined as "Students' belief that they can achieve well in science" (Lawson, Banks and Logvin, 2007 as cited in Glynn et al., 2009). The Science Motivation Questionnaire –II has five items for measuring self-efficacy with the response of each item related by using rating scale of temporal frequency: never (0),

rarely (1), sometimes (2), often (3) or always (4). The score range for each of the five items of the scale is 0-20 (Glynn et. al., 2009). The original scale reported a reliability estimate Cronbach's alpha coefficient of 0.9. Sample items of this scale are "I am confident I will do well on science tests" and "I am confident I will do well on science labs and projects".

Statistical Analysis:

Owing to the ordinal type of the data obtained from the tool, it was validated using the fresh approach of network psychometrics (Johal and Rhemtulla, 2023) using R version 4.2.3 (2023) and RStudio version 2023.12.0+369 (2020). Exploratory graph analysis (EGA) to extract the cluster, estimate its structural consistency and ordinal confirmatory factor analysis were conducted using *EGAnet* package (Hudson and Alexander, 2024). The plots of regularized network, centrality indices, edge-weight accuracy confidence, correlation stability, edge difference, node difference and node predictability were generated using *bootnet* (Epskamp, Borsboom and Fried, 2018), *qgraph* (Epskamp et al., 2012), *psychTools* (Revelle, 2024) and *mgm* (Haslbeck and Waldrop, 2020) packages.

Results:

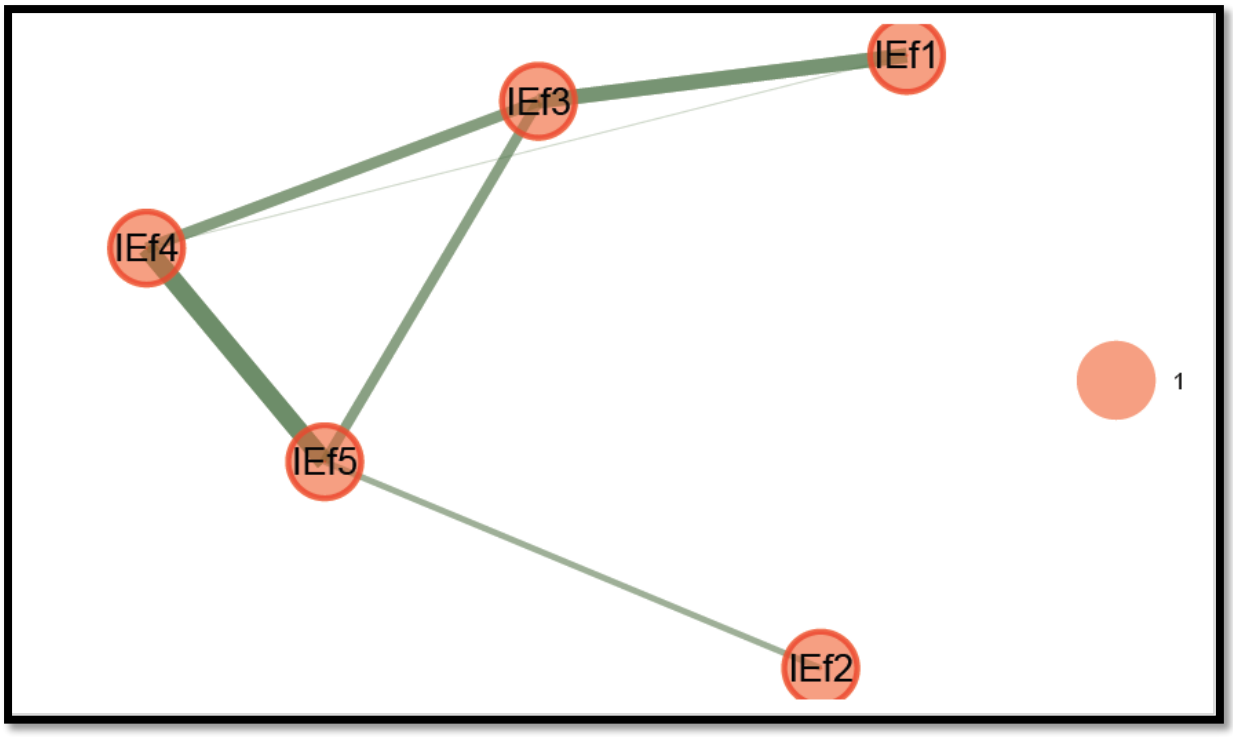

Fig.1 Pair-wise Markov Random Field or Gaussian Cluster of Science Self-Efficacy

The exploratory graph analysis (EGA; Golino and Epskamp, 2017) using the default Glasso technique extracted a single cluster with all the five nodes in it. Node 1 and Node 2 are related to Node 3 and Node 5, while the nodes 3, 4 and 6 are interrelated to each other.

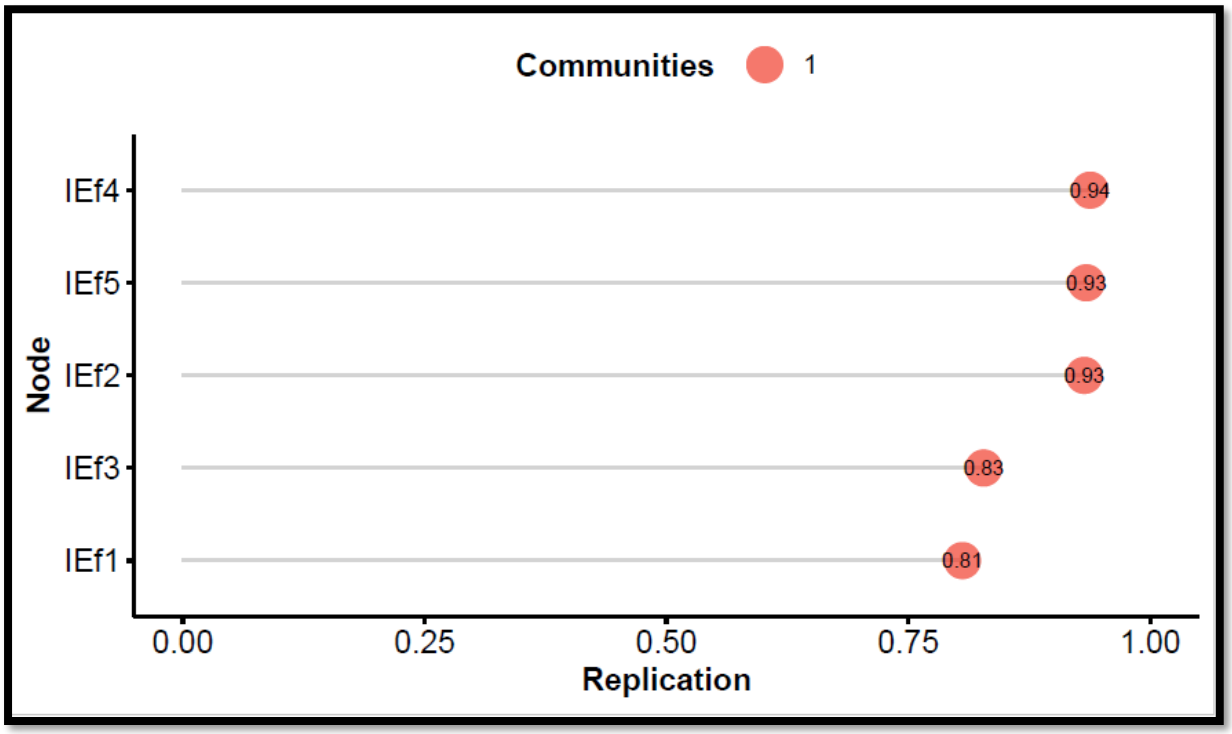

Fig.2 Structural Consistency of the nodes of Science Self-Efficacy Network

Node 4 was found to be related to network 94 % of time when checked in the bootstrapped samples generated through 500 iterations using the sample data. Nodes 5 and 2 showed this tendency 93 %. Node 3 associated with the science self-efficacy cluster 83 % of times when searched for it in the bootstrapped samples. Node 1 emerges as the weak element of the network whose estimate of binding with it is 81% during multiple replications of bootstrapped samples. Overall, the entire network with five nodes has the estimate of dimensional stability at 0.744, quantitatively representing the structural consistency of the network (Christensen, Golino and Silvia, 2020).

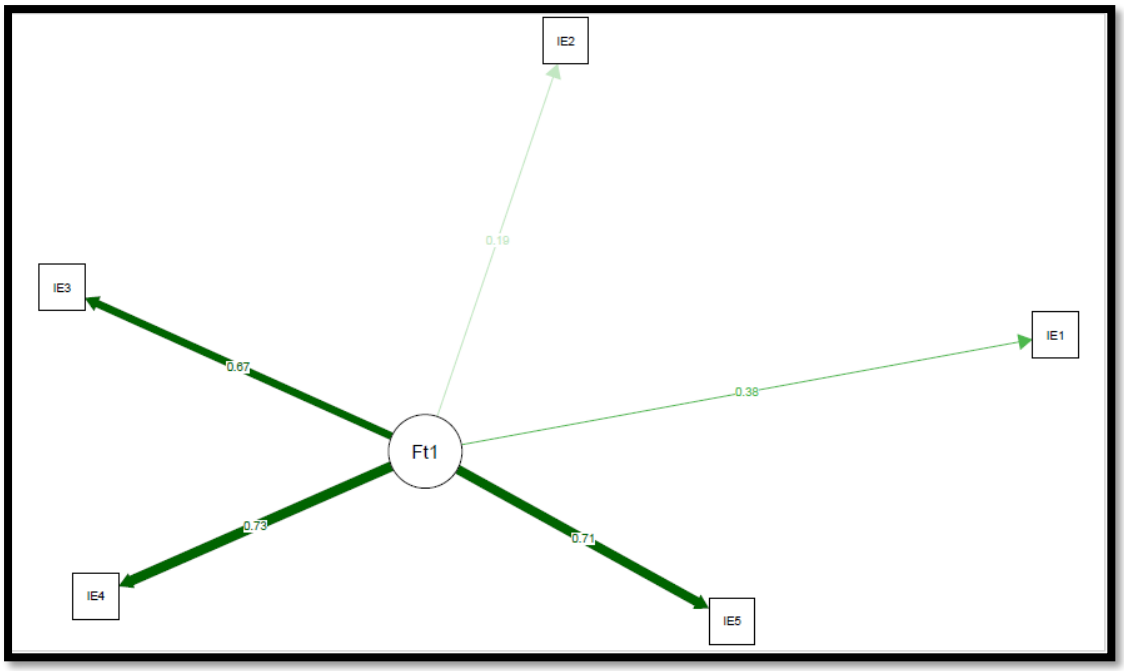

Fig.3 Loadings of the nodes of Science Self-Efficacy Network

The loadings of a network are similar to the loadings of the factor (Christensen and Golino, 2021). Hence node 4 loads on the network with highest magnitude of 0.73 followed by node 5 and 3 with magnitudes of 0.71 and 0.67 respectively. Node 1 loads on the network weakly at 0.38. Node 2 is the weakest element with 0.19 loading estimate.

The ordinal confirmatory factor analysis using weighted least square mean variance (WLSMV) estimator found the goodness of fit estimates of the network using *lavaan* package (Rosseel, 2012). The comparative fit index (CFI) was 0.99. The Tucker-lewis index (TLI) was 0.98. The root mean square error of approximation (RMSEA) was 0.051 and the standardized root mean square residual (SRMR) was 0.068. These estimates describe the goodness of fit when the data is assumed to be interval type generally estimated using Maximum likelihood (ML) estimator. The ordinal counterparts of these estimates obtained were the CFI.robust = 0.954, TLI-robust=0.908, srmr.bentler=0.047 and rmsea.robust=0.086. While CFI and TLI estimates are expected to be higher than the benchmark of 0.9, the SRMR and RMSEA can be treated to be acceptable when their estimates are less than 0.05 and 0.08 respectively (Hooper et al., 2008). Even for a fairly low sample size of the present study, the obtained estimates decent enough to indicate the construct validity of the network.

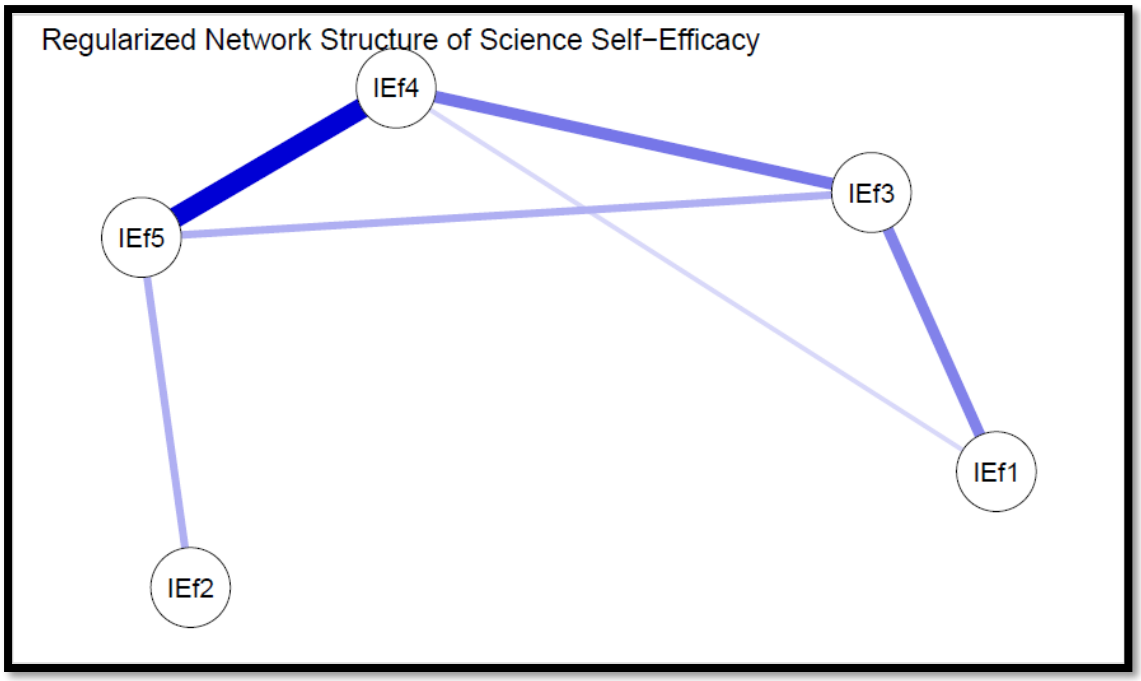

Fig.4 Regularized Network Structure of Science Self-Efficacy

The Least Absolute Shrinkage and Selection (LASSO) operator based regularized network structure represents only the strongest of the connections among the nodes of the network, reducing the weakest connections to zero. For networks with lesser nodes, the number of edges is also small and hence the regularized network is akin to the initially obtained network structure. Most importantly, the regularized network formally represents a unique ecosystem or the very construct of science self-efficacy, through its constituent nodes and their signature inter connections (Constantini et al., 2014). The stability and reproducibility aspects of the obtained network are addressed in the further analysis.

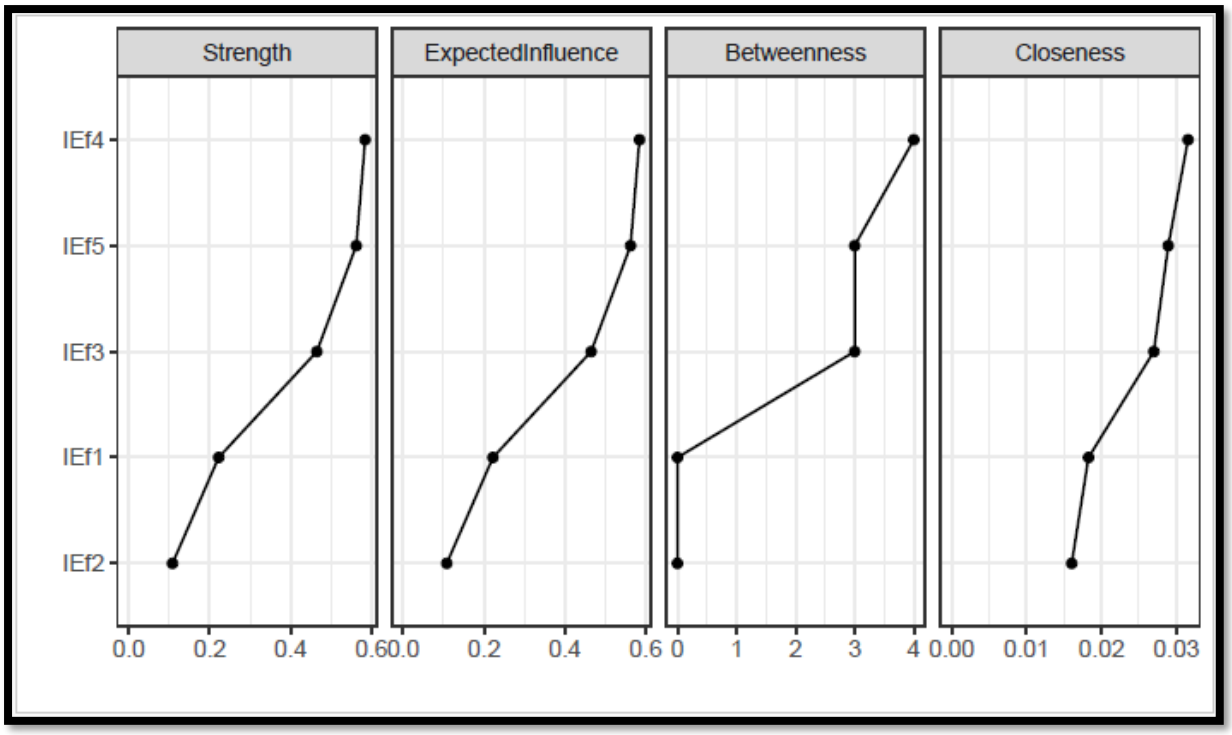

Fig.5 Centrality Indices of the Network Structure of Science Self-Efficacy

The quantitative description of the network is done by estimating three important network parameters of strength, closeness and betweenness of its nodes. Node 4 is the very important element of the network with respect to these parameters and node 2 is the least important entity.

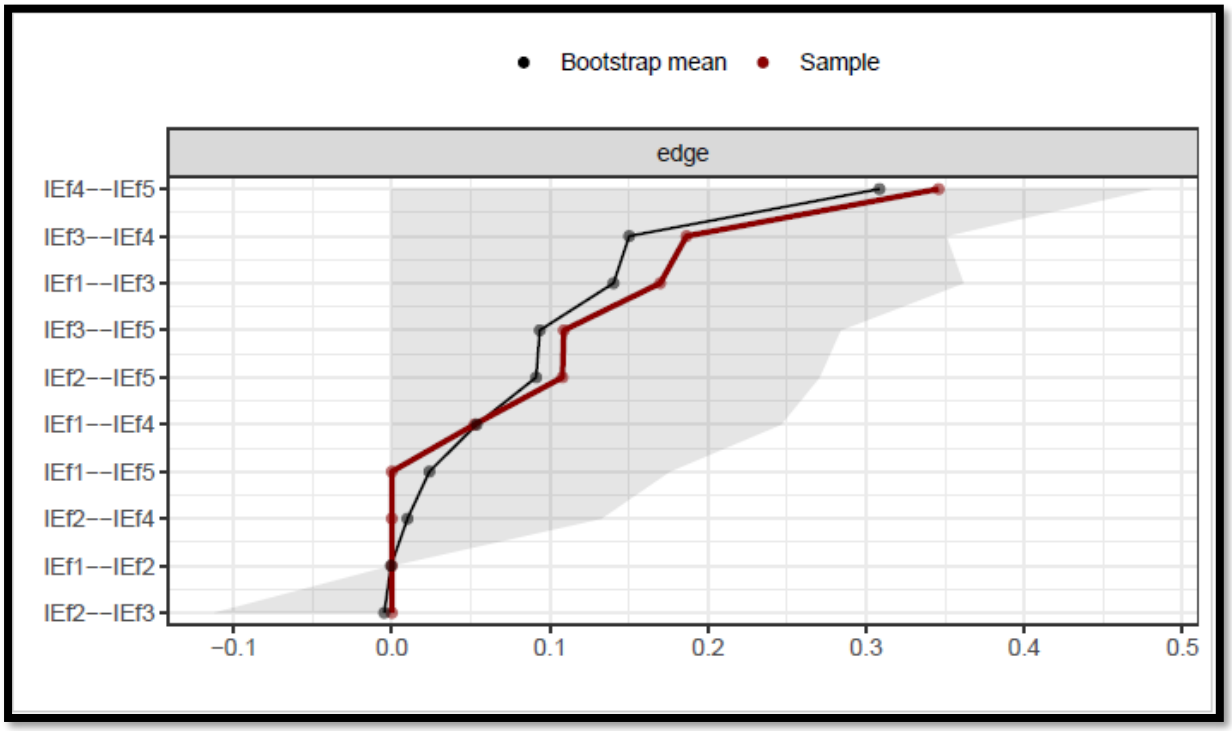

Fig.6 Edge-weight Accuracy Confidence Interval Plot of the Network Structure of Science Self-Efficacy; The red line stands for the sample data and the black line represents the bootstrapped data with the grey region showing the confidence interval width

The edges are the graphically representation of the strength of the relationship between two nodes in the network and statistically are partial correlation coefficients controlling the influence of others nodes of the network. These edges are arranged in the decreasing order of their strength in the network and compared in multiple samples generated using the iterative bootstrapping techniques from the sample data. A confidence interval plot reveals whether this ordering of the edges can be interpreted with caution or not based on the presence or absence of zero between the lower and upper limits of the confidence interval. Presence of zero between the confidence interval indicates a non-significant result, as is the case in the present study, indicating no difference in the ordering of the edges with respect to their strength in the sample and bootstrapped data. The edge connecting nodes 4 and 5 are the strongest in the entire network, and the edge relating node 2 to node 3 is the weakest one.

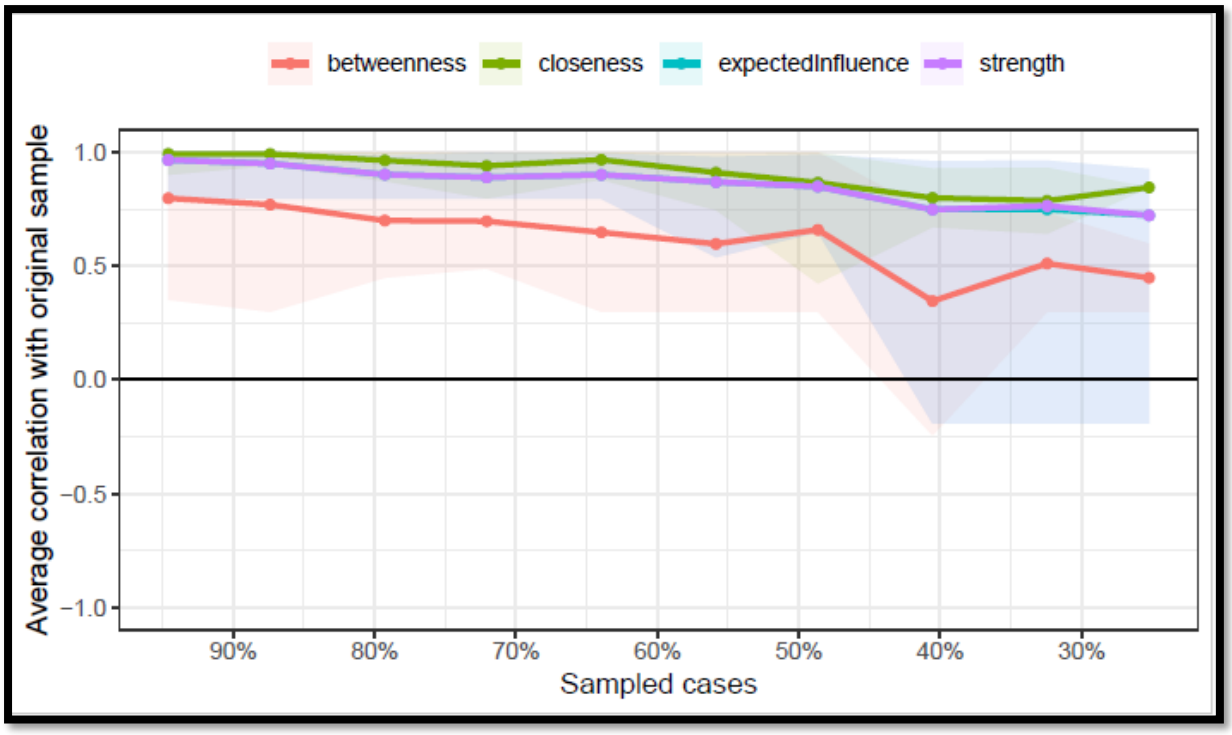

Fig.7 Correlation Stability Plot of the Network Structure of Science Self-Efficacy

The CS-coefficient estimates the relationship between the obtained network and network obtained on the successive dropping of the cases or reducing the sample size by 10 percent in every time using the bootstrapping technique. A very straight or stable purple line indicating strength attribute of the network implies that the formation of the present network took place for a way lesser sample size further testifying the replication of the network in further studies. It is quantitatively represented through the CS-coefficient, which in this study is obtained poor at 0.126 for the benchmark of 0.2 to 0.5 at least (Epskamp and Fried, 2018), due to low sample size of 110.

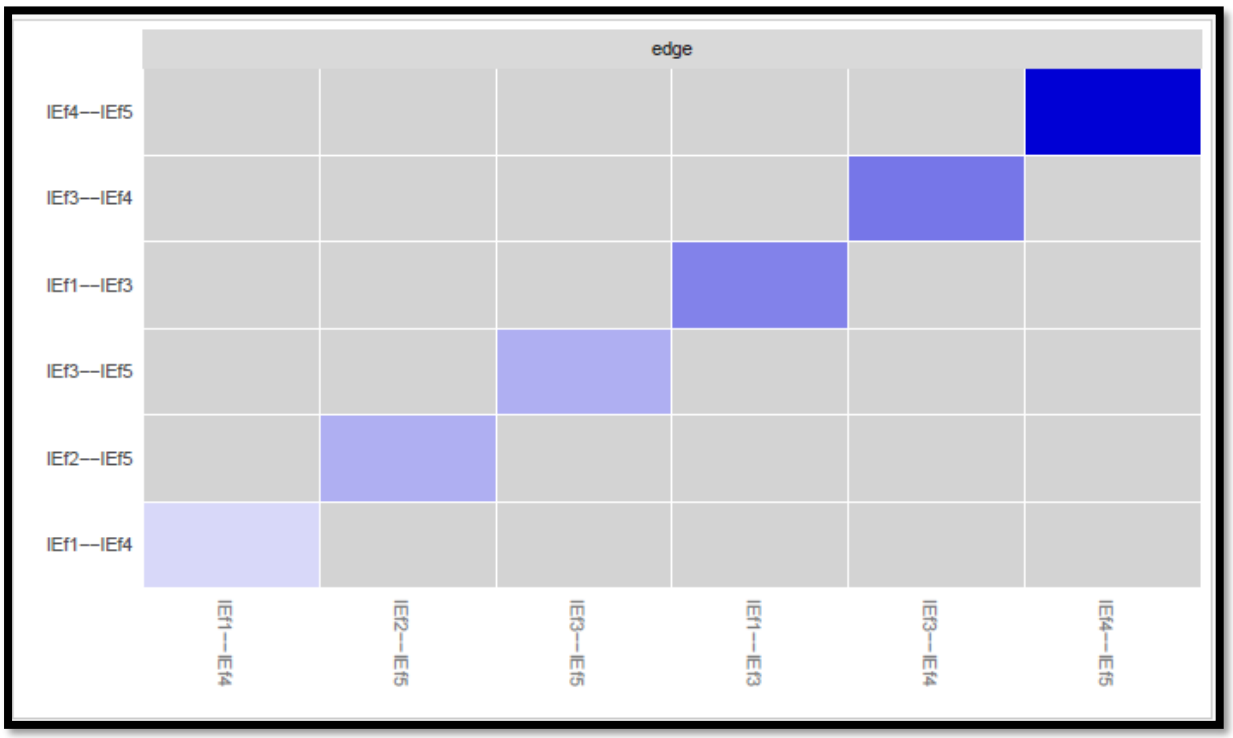

Fig.8 Edge Weights Difference Test Plot of the Network Structure of Science Self-Efficacy; Grey boxes show non-significant results

The edges of the network do not significantly differ from each other with respect to their strength.

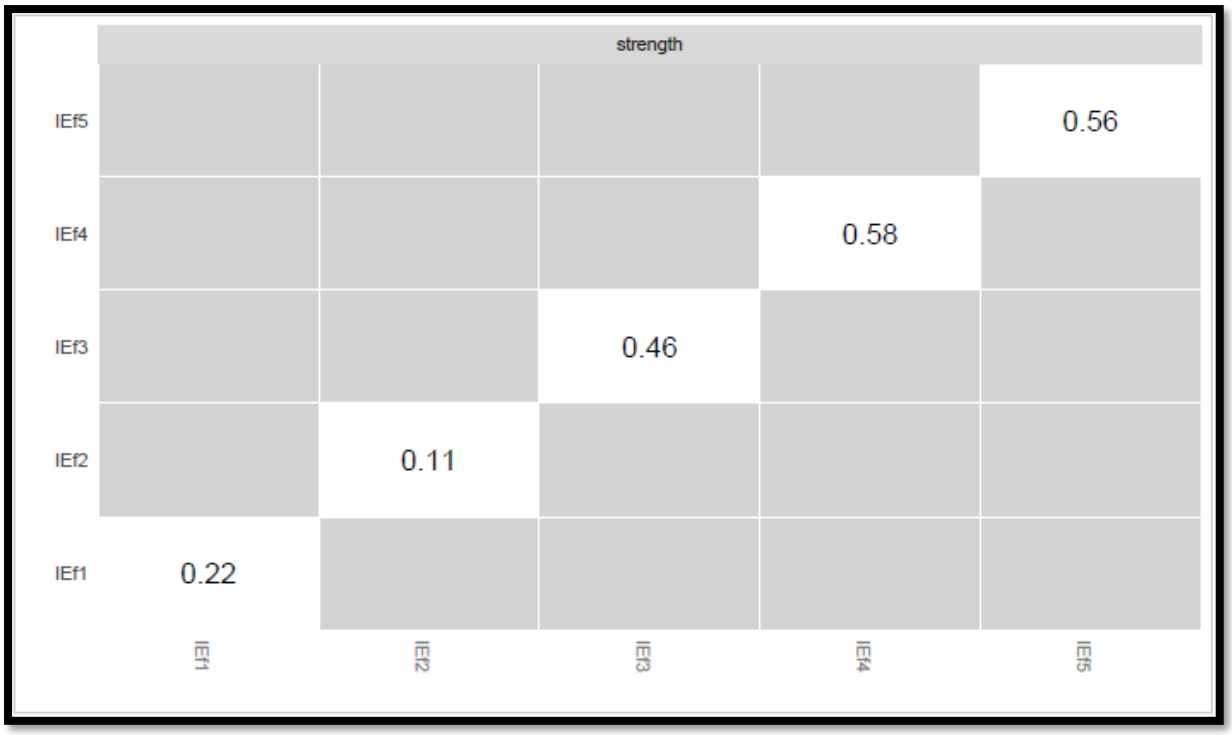

Fig.9 Node Difference Test Plot of the Network Structure of Science Self-Efficacy; Grey boxes show non-significant results

The nodes of the network do not significantly differ from each other with respect to the characteristic strength.

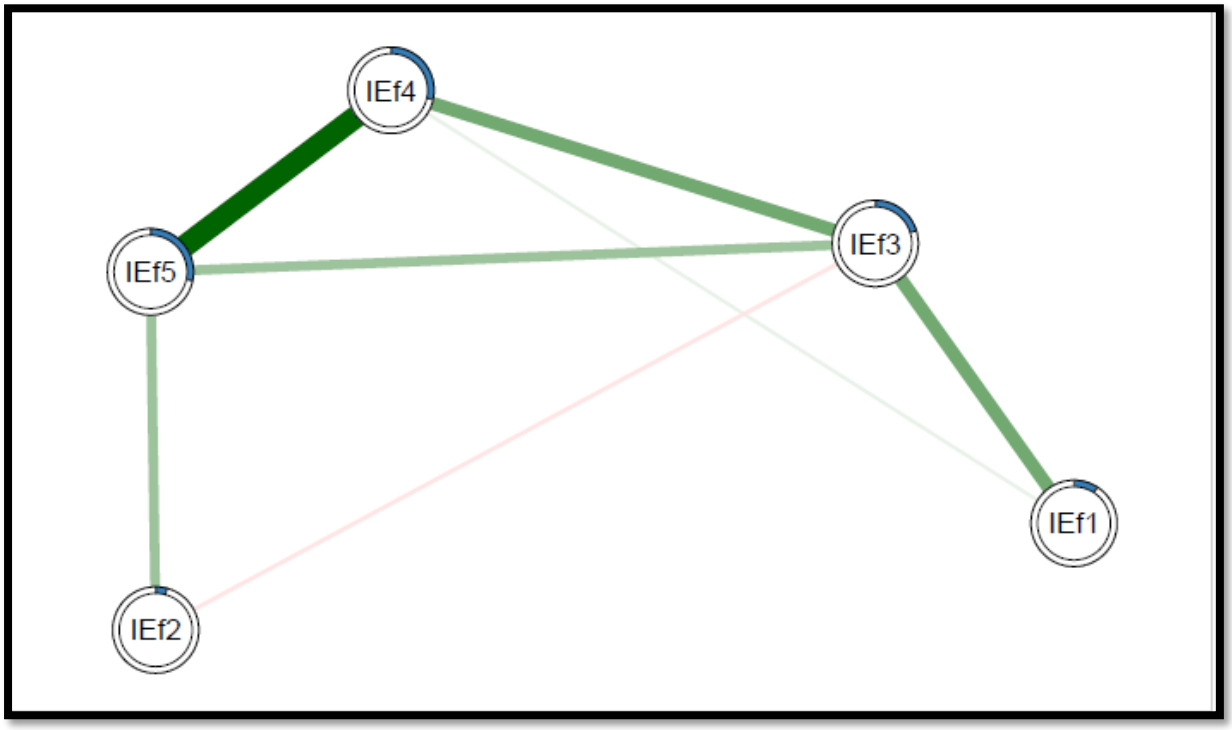

Fig.10 Node Predictability Plot of the Network Structure of Science Self-Efficacy

The extent to which a node is predicted to be part of the network by the other nodes is represented graphically and statistically using node predictability (Haslbeck and Waldrop, 2018) R^2. In the present study, nodes 4 and 5 were predicted by 28.5 % and 28.4% nodes of the network, followed by node 3 at 20.2%. Nodes 1 and 2 were almost not predicted by any of the neighbouring nodes since their predictability estimates were very low at 9.2% and 4.3%.

Discussion:

There are several scales to measure general (Schwarzer and Jerusalem, 1995), academic (Dullas, 2018), discipline-specific self-efficacy (Uzuntiryaki and Çapa Aydın, 2009) in students of school (Thompson, Anderson and Nashon, 2007) and college (Glynn and Kobala, 2006) level education and in multiple cultural contexts (Mohd Dzin and Lay 2021) as well. However, the need to develop parsimonious tools to measure this important trait exists, since its research is conducted in conjunction with other pertinent variables towards the development of robust discipline, context and population specific quantitative psychological models. Presence of variables measured using length items representing their respective dimensions, increase the number of parameters in the model, making it more complex.

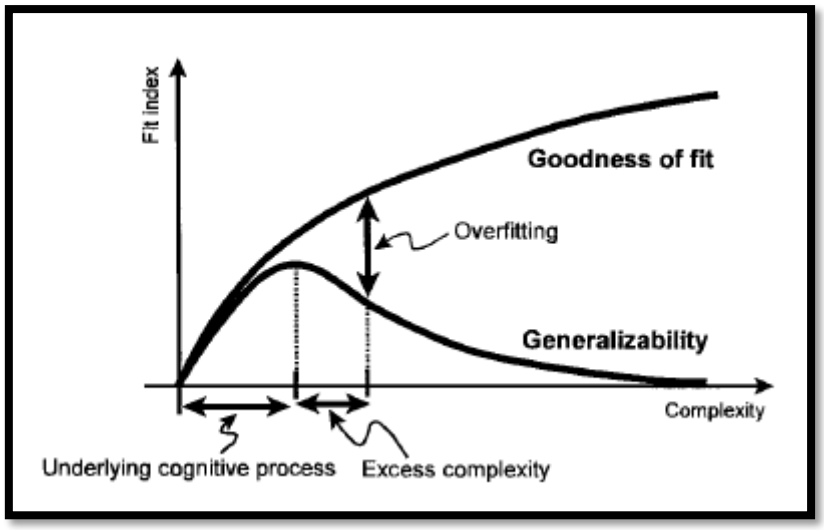

Fig. 11 Relationship between Goodness of fit, Model Complexity and Generalizability of Findings (Myung and Pitt, 2001)

Rise in complexity of the model, increases the chances of over fitting of data during model selection / validation studies, inflate goodness of fit, and can adversely impact the generalizability of the model findings (Pitt, Myung and Zhang, 2002). A model fit happens not only because the proposed models are true, but also owing to the model

over fitting the data. It is because quantitative data is made up of signal and error parts respectively. A good fit between the model and data happens when the signal part of the data is stronger than the error part. Model over fitting happens when the error part is stronger than the signal part. In both these scenarios, the goodness of fit continues to rise. While in the former case, rise in goodness of fit represents actual validation of the model leading to generalizability of the findings, in the latter case of model over fitting, goodness of fit is inflated instead and the study results in such a case do not get replicated in future studies (Vandekerckhove, Matzke, and Wagenmakers, 2015).

To address such an important aspect of psychometrics through the validation of parsimonious tools, the present study validated the five items science self-efficacy scale pertinent in STEM education research using network psychometrics. Even for a relatively smaller sample size and being foreign in origin, all the items of this scale indicated being part of their intended construct. This advancement is first of its kind in the Indian context as far as the knowledge of the authors is concerned. The work can contribute in conducting studies which can explore, relate and validate important STEM education variables in the context of high school level education to form robust measurement models. Presence of such empirical models can help the academic practitioners and stakeholders to construct effective intervention programs for the development of genuine interest in science subject and STEM careers in general.

The study although has its share of limitations. The subjects belonged to a very restricted geographical area, from a primer institution of education in the Bhubaneshwar city, Odisha state, India. Also, the sample size was small. Hence, the findings of this study can be generalized only after replications happen in other culturally diverse part of this country on the same population.

Conclusion:

The present study tried to provide a robust and parsimonious tool to measure the critical STEM education variable of science self-efficacy in a very important population of high school students in the Indian context. It is hoped that the availability of such a tool can promote the research on this variable in the country leading to the development of effective intervention programs cultivate this trait in the intended students.

Ethics Statement: The entire work was conducted as per the guidelines to be followed during data collection in Ph.D. works as laid down by the Institutional ethics committee,

Lovely Professional University, Phagwara, India, with its approval for the same, bearing reference number *LPU/IEC-LPU/2024/2/34*

Author Contributions: First author gathered the data and conducted data analysis, the second author wrote the manuscript and the third author supervised the entire study.

Conflict of Interest Statement: The authors declare no conflict of interest.

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