Validation of Cognitive Absorption Model Based Science Academic Flow Scale in the Indian Context: A Network Psychometrics Approach Analysis

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ABSTRACT

The present study was conducted to validate the Cognitive absorption model (El-Mawas and Heutte, 2019) based Science Academic Flow Scale in the Indian context. The sample of the study comprised of 342 (213 Girls and 129 Boys) secondary school students belonging to grades 9^{th} and 10^{th} of a school in the Andhra Pradesh state of India. Considering the ordinal level of the data obtained in this cross-sectional survey design study, the novel approach of Network Psychometrics was chosen to validate the four factors structure of the construct flow particularly in science academic context. RStudio/R Ver 4.2.3 was used for conducting the statistical analysis. Exploratory graph analysis (EGA) performed at the item/node level, using the function *bootnet*, revealed the nine nodes of Cognitive absorption form a cluster and the remaining three nodes of autotelic experience form another cluster. The network existing between the four dimensions/clusters of science academic flow was explored. The ordinal confirmatory factor analysis results displayed excellent estimates of robust goodness of fit indices. Structural consistency exercise revealed all four clusters being part of a single network of science academic flow. The regularized network of the model was obtained using the function *bootnet*. It was followed by obtaining of the centrality indices, edge weight confidence interval and correlation stability of the network using *qgraph* function. Implications of the study with respect to school education and psychometric practices are discussed.

Keywords: *Cognitive Absorption Modeling, Exploratory Graph Analysis (EGA), Network Psychometrics, Ordinal Confirmatory Factor Analysis, Science Academic Flow, Science Academic Flow Scale, Structural Consistency*

Introduction:

The phenomenon of flow, first proposed by Mihaly Csikszentmihalyi in 1975, involves individuals getting completely absorbed in the execution of an activity for the sake of the activity itself and without the presence of any external reward. The individuals direct all their efforts in continuing with that highly desirable state. The experience gets initiated whenever there is a balance between the skill required to execute an activity by an individual and the challenges offered by the activity in a certain learning environment. According to EFRN (2014), flow, also known as optimal experience is defined as “a gratifying state of deep involvement and absorption that individuals report when facing a challenging activity and they perceive adequate abilities to cope with it”. The complete and intense concentration associated with the flow experience, ensures that the activity in which the individual is involved, is carried out to optimal efficiency and is gets progressively refined due to the consistent efforts placed by the individual due to intrinsically rewarding aspect. Balance of the skill and challenge associated with an activity makes the task not only rewarding but also pushes the capabilities of the individual, leading to a heightened sense of self-esteem (Csikszentmihalyi and LeFevre ,1989). Positive consequences of balance between perceived skill and perceived challenge hence make the flow construct a critical academic variable to be explored in depth along with its role in enhancing learning.

Education is one of the eight major themes in which the concept of flow has been studied according to the literature of flow, besides studies on its mechanism, impact on health, positivity, technology, ports, gaming and creativity (Zhang and Wang, 2024). Flow in the context of academics, is studied through the construct of academic flow. Initial studies of flow in academic context found it to be related to the indicators of motivation, with Social Cognitive Theory (Bandura, 1986) in the backdrop, like goal orientation (Oertig et al, 2014), intrinsic motivation (Keller et al, 2011), self-efficacy (Rodríguez-Sánchez, 2011), future time perspective (Elias et al, 2010), and academic procrastination (2005). Heutee et al. (2014, 2016) found that the heightened sense of self-efficacy has a positive effect on the flow experience in academic contexts establishing the direct link between flow and learning, by proposing the *Eduflow* model. This model also provided a multidimensional short scale to measure flow in educational context or academic flow. However, it was realized that this scale measured recalled flow as opposed to measuring the flow at the time of activities in cross-sectional design studies (Culbertson et al., 2015).

This observation led to the development of the second version of Eduflow scale by El-Mawas and Heutte (2019) with 12 items and seven point likert scale for registering the responses of the subject. This model consisted of four dimensions namely, cognitive control, immersion and time transformation, loss of self-consciousness and autotelic experience. The first three dimensions represented Cognitive absorption which predicted the fourth dimension of autotelic experience, which is known as the Cognitive Absorption Modelling (Heutte, 2017).

According to Hamash et al., (2024), there are immense potential in conducting research by clubbing flow with STEAM education. Zausmer et al. (2024) showed that the way leaning conditions are designed strongly impact the teachers' flow-state as well along with that of the students. These recent findings further provide impetus to the conducting of present research study to make available a robust tool to measure the state of flow in the context of science education. The present study tried to address the gap of the non-availability of a robust, short and science domain specific instrument to measure academic flow during STEM classrooms in India by validating the Science version of Academic Flow scale using the novel network approach through the extension of the work of El-Mawas and Heutte (2019).

METHODOLOGY

Descriptive cross-sectional research design using survey method was adopted for the present study. Secondary school students of 9th and 10th grade were the population of this study since it is from these grades, that the students are rigorously prepared to appear for a nation-level entrance exam to qualify and seek admission to pursue engineering and technology programs from reputed Indian Institutes of Technology or seek sciences at graduation level, after completing their 12th grade in India. Display of academic flow at these STEM preparatory stages during science classes can increase the academic performance of these students (Akyol and Kabasakal, 2023) further increasing the chances of their future academic performances.

Sample:

The sample of the study comprised of 342 (213 Girls and 129 Boys) secondary school students belonging to grades 9th and 10th of a school in the Andhra Pradesh state of India. 62.28 % subjects were girls and 37.71 % subjects were boys. 200 (58.47 %) of them belonged to 9th grade and the remaining 142 (41.52 %) belonged to 10th grade. The average age of these subjects was 14.5 years.

Instrument:

Measurement of Science Academic Flow:

The Eduflow scale developed by El-Mawas and Heutte (2019) was adapted in the context of science education for secondary school students by the investigators. All the 12 items of the Eduflow scale, with three items each of cognitive control, immersion and time transformation, loss of self-consciousness and autotelic experience dimensions, were changed to make them science class specific and are presented below:

Table 1: Items of the Eduflow scale and Science Academic Flow Scale

S.No.	Items of Eduflow Scale	Items of the Science Academic Flow Scale
1	"I trust my ability to meet the high demands of the situation"	"I trust my ability to meet the high demands of the science classroom situations"
2	"I am wholly absorbed in what I am doing"	"I am wholly absorbed in what I am doing during a science class."
3	"I don't care about what others may think of me"	"I don't care about what others may think of me in a science theory class."
4	"I have the feeling I am living a very exciting experience"	"I have the feeling I am living a very exciting experience during a science class."
5	"I feel completely in control of my actions"	"I feel completely in control of my actions in a science class"
6	"I am deeply focused on what I am doing"	"I am deeply focused on what I am doing, while performing a science activity."
7	"I am not concerned about the judgement of others"	"I am not concerned about the judgement of others of me as a science student."
8	"This activity brings me a sense of well-being"	"Science activities bring me a sense of well-being."
9	"At each step, I know exactly what I have to do"	"At each step, I know exactly what I have to do in a science class."
10	"I am losing track of time"	"I am losing track of time in a science class."
11	"I am not worried about what others might think of me."	"I am not worried about what others might think of me in a science practical class."

12	"When I talk about this activity, I feel such a deep emotion that I want to share it."	"When I talk about science activities, I feel such a deep emotion that I want to share it with others."

The above mentioned statements were shown to highly experienced government school teachers teaching the science subjects of Mathematics, Physics and Biology to secondary school students to seek content validity. The language of the items was reviewed by a government school English teacher. The scale was also validated for its content by a faculty of Educational Psychology working in a state university. All the responses of the scale were collected using 7-point Likert scale where 1 = Strongly disagree and 7 = Strongly agree.

Statistical Analysis

The measures of central tendency, dispersion, relationships and asymmetry were estimated for the four dimensions of cognitive absorption model, using SPSS Statistics Ver. 23.0. Content validity was quantitatively estimated through the detection or the presence of the Floor and Ceiling effects (McHorney and Tarlov, 1995) where the percentages of extreme response score of the subjects were checked to be below the threshold of 15 % or not using Microsoft Excel 2010 package.

The cognitive absorption model based on which the science academic flow scale is developed, was validated using the novel approach of Network Psychometrics (Golino and Epskamp, 2016), considering the ordinal data level of responses obtained from survey questionnaires, using R/RStudio Ver. 4.2.2. packages of *EGAnet, lavaan, bootnet, qgraph* and *psychtool*. Also, the Cognitive absorption model is built from a latent variable perspective where the dimensions, cognitive control, immersion and time transformation, loss of self-consciousness form cognitive absorption which in turn linearly predicts the fourth dimension of autotelic experience, in a rather simplistic way. However, under network approach, a phenomenon like science academic flow is considered to be an outcome of complex interactions of multiple dimensions associated with that phenomenon, graphically represented as a network and psychologically forming an ecosystem, where certain elements interact in a manner to stimulate the phenomenon while other elements interact with each other to inhibit it (Constantini et al, 2014). Hence, the application of network psychometrics on the data of science academic flow was expected to present deeper insights into the complex interactions among its dimensions.

Procedure of Data Collection:

Prior permission from the head of the school situated in Vijaywada city of Andhra Pradesh state, India was taken. The investigator physically visited the selected school for data collection. The head of the school was explained the purpose of the visit and provided a formal request for data collection from the students of the grades of 9th and 10th classes of the institution. After explaining the purpose of the visit to the head and providing the assurance of confidentiality of the data of the school students and its usage solely for research purposes, the points of voluntary participation, use of the research, voluntary participation and right to disengage from any stage of data collection, in the informed consent letter was read before the participants. Those students who provided their verbal consent were selected for the study as inclusion criteria and those who declined, were not considered for the study forming the exclusion criteria. The head of the institution signed the informed consent letter on the behalf of the participating students. Then physical copies of the questionnaire were distributed to the subjects while the classes were in session and the help of the school teachers taking the class was sought in the smooth administration of the questionnaire and collection of the same. The students took 15 minutes of average to complete the task. The final sample size was 342. Prior to data collection, ethical approval was obtained from the Institutional Ethics Committee of the Lovely Professional University, under approval number EC/NEW/INST/2022/3110.

RESULTS

Descriptive Statistics:

For detecting outliers, Mahalanobis distance was estimated for the gather data. No outliers were detected. Then, the measures of central tendency, dispersion and asymmetry of the four dimensions of the cognitive absorption model of the science academic flow scale, were estimated using mean, standard deviation, skewness and kurtosis estimands, followed by measure of relationship through Pearson Product Moment Correlation coefficients of the items, using SPSS Statistics Ver 23.0. and the obtained estimates are displayed below:

Table 2: Descriptive Statistics

Dimension	Mean	Std. Deviation	Skewness	Kurtosis
Cog_Control	5.3470	1.15434	-0.948	0.864
Imm_Time_Trans	5.1481	1.17795	-0.509	-0.450

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Loss_of_Self_Con	5.4610	1.16353	-0.951	0.372
Autotelic_Exp	5.3791	1.14058	-0.771	0.122

Table 3: Measure of Inter-Item Relationship Estimated using Pearson's Product Moment Correlation Coefficient:

		Cog_Control	Imm_Time_Trans	Loss_of_Self_Con	Autotelic_Exp
Correlation	Cog_Control	1.000	.450**	.435**	.455**
	Imm_Time_Trans		1.000	.361**	.302**
	Loss_of_Self_Con			1.000	.390**
	Autotelic_Exp				1.000
** - Result is highly significant at 0.01 level					

Table 4: Estimates of Floor and Ceiling Effect:

S.No.	No. of Subjects with Lowest Score of the Scale of 12	No. of Subjects with Highest Score of of the Scale 84	Total Subjects	Floor Effect Estimate	Ceiling Effect Estimate	Benchmark of Acceptance	Result	Remark on Item Floor or Ceiling Effect
1	0	2	342	0 %	0.584%	15%	Both Floor and Ceiling effects estimates are less than the benchmark	***Absent***

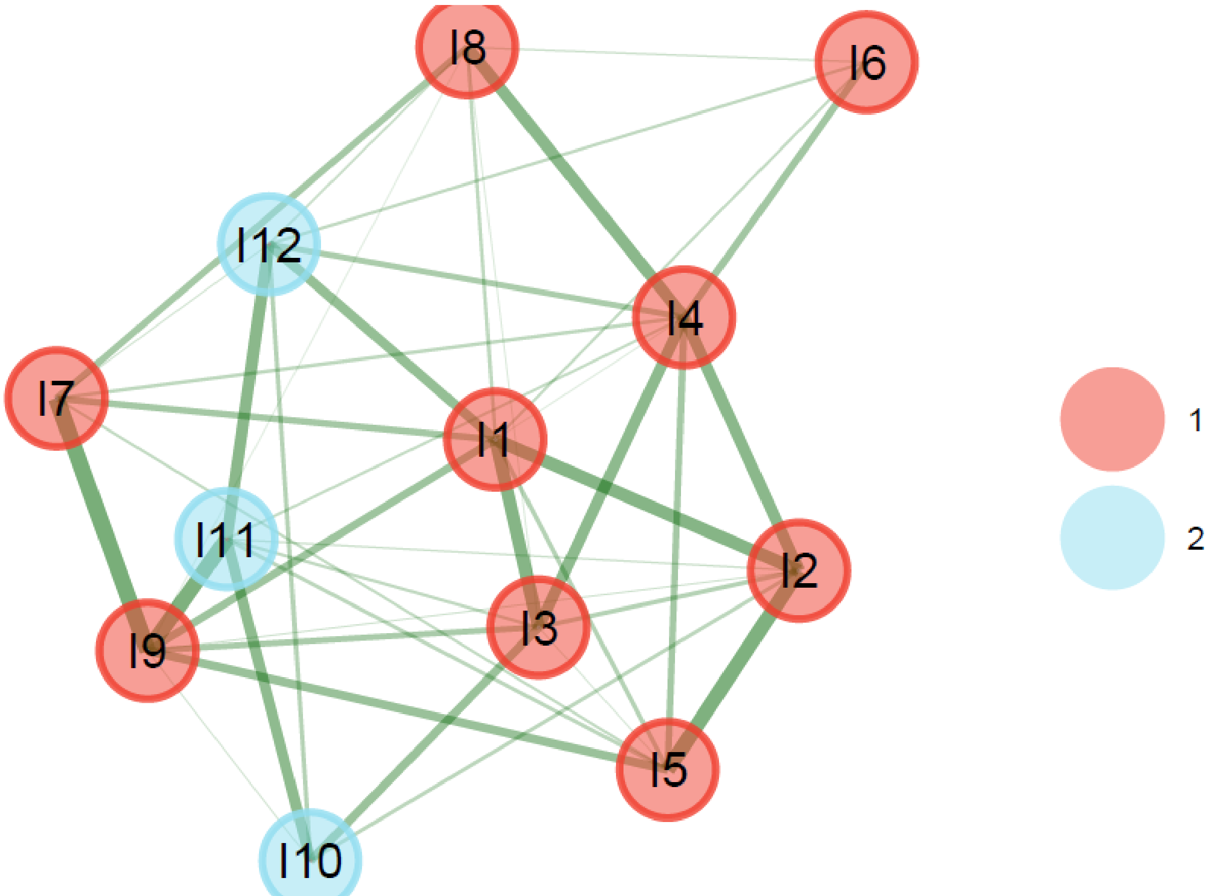

Fig. 1: Network Structure of the Cognitive Absorption Model based Science Academic Flow Scale Nodes at Dimension Level at Item Level, 1 = Cognitive Absorption and 2 = Autotelic Experience

Using the R/Rstudio Ver. 4.2.3 package of *bootnet*, the technique of exploratory graph analysis (EGA) was applied on the collected data items. The obtained network shown in *Fig.1*, has two clusters, with the nine nodes forming the first cluster of Cognitive absorption and the remaining three nodes forming the second cluster of autotelic experience.

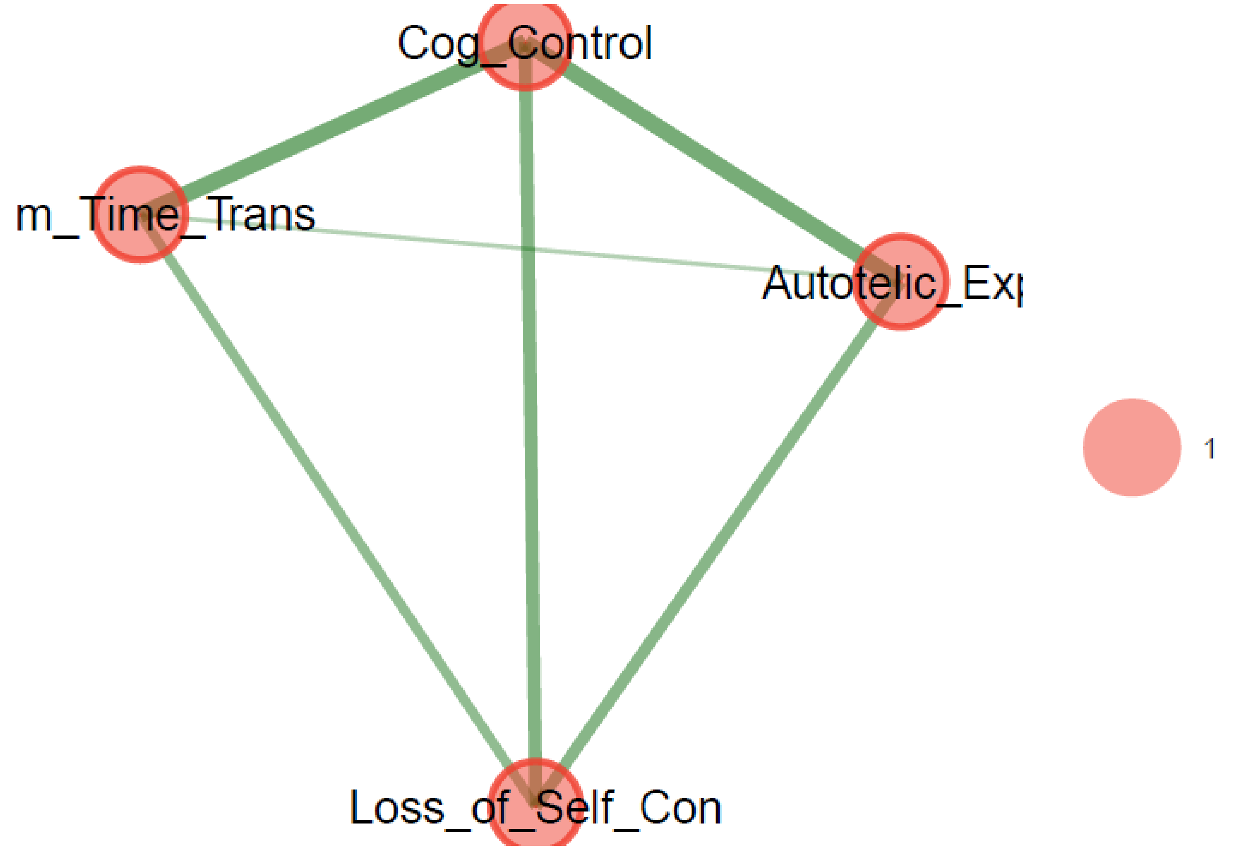

Fig. 2: Network Structure of the Cognitive Absorption Model based Science Academic Flow Scale Nodes at Dimension Level

The exercise of exploratory graph analysis was again run with the data of the four dimensions of the science academic flow scale as per the Cognitive absorption model. It resulted in obtaining of a single cluster network, representing the science academic flow construct, where its dimensions as nodes of the network, were complexly related to each other, as shown in *Fig.2*, in contrast to the simplistic linear relationships displayed in El-Mawas and Heutte (2019) scale. The nodes of cognitive control, immersion and time transformation, loss of self-consciousness are interrelated to each other, forming cognitive absorption, and these three nodes are related to the fourth dimension of autotelic experience. However, the strength of the connection between the node immersion and time transformation, and the node autotelic experience is relatively weak.

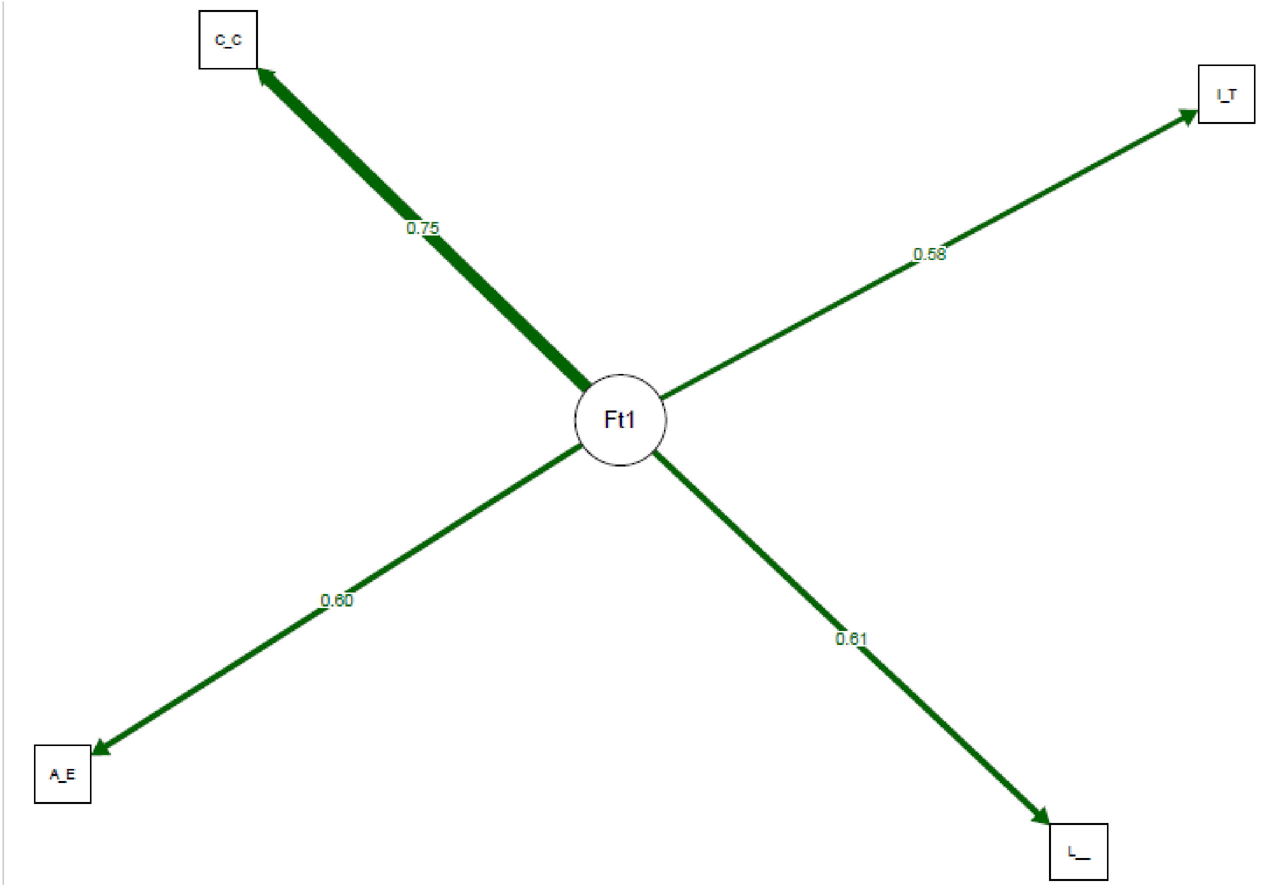

Fig.3: Ordinal Confirmatory Factor Analysis Structure of the Cognitive Absorption Model based Science Academic Flow Construct

Table 5: Goodness of Fit Estimates of the Ordinal Confirmatory Factor Analysis of the Science Academic Flow Construct Network Structure

	CFI (For Interval Data)	**Robust CFI (For Ordinal Data)**	**TLI (For Interval Data)**	**Robust TLI (For Ordinal Data)**	**RMSEA (For Interval Data)**	**Robust RMSEA (For Ordinal Data)**	**SRMR (For Interval Data)**	**SRMR Bentler (For Ordinal Data)**
Benchmark (Hu and Bentler, 1999)	>0.95	>0.95	>0.95	>0.95	<0.05	<0.05	<0.08	<0.08
Obtained Estimates From R Version 4.2.2	0.995	0.997	0.986	0.991	0.041	0.032	0.016	0.016

The obtained estimates quite satisfy their respective benchmarks as per the goodness of fit standards set by Hu and Bentler (1999). This result verifies the cognitive absorption model based science academic flow scale with its 12 nodes / items and four dimensions / clusters. The factor loadings of the nodes cognitive control, immersion and time transformation, loss of self-consciousness and autotelic experience on science academic flow construct are strong enough at 0.75, 0.58, 0.61 and 0.6 respectively.

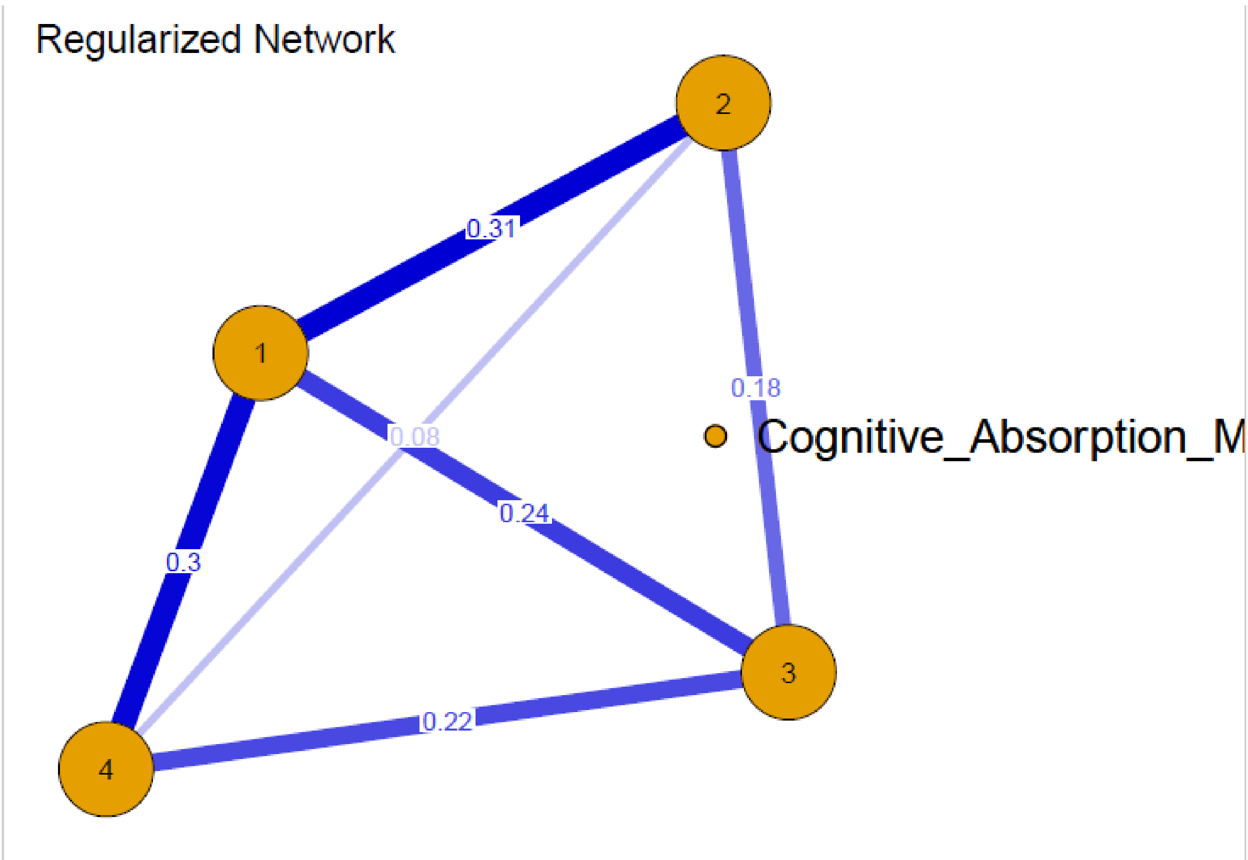

Fig.4: Regularized Network of Cognitive Absorption Model based Science Academic Flow Scale

Node 1 in the regularized network is cognitive control. Node 2 is immersion and time transformation. Node 3 is loss of self-consciousness and node 4 is autotelic experience. It is evident that the strength of the connection (edge) between the node 2 of immersion and time transformation, and the node 4 of autotelic experience is weak at 0.08. The strengths of the edges connecting other nodes of the Cognitive absorption modeling network are relatively stronger.

Table 6: Loadings of the Nodes in the Network Structure

Node	Network Loading (Partial Correlation Coefficient of the Edge)
Cog_Control	0.505
Loss_of_Self_Con	0.379
Autotelic_Exp	0.354
Imm_Time_Trans	0.335

In order to estimate the stability of the obtained network, the package *qgraph* was used to get the measures of the centrality indices of the network.

Centrality Metrics Analysis using *bootnet* (Epskamp, Borsboom and Fried, 2018) and *qgraph* R (Epskamp et al., 2012) Packages:

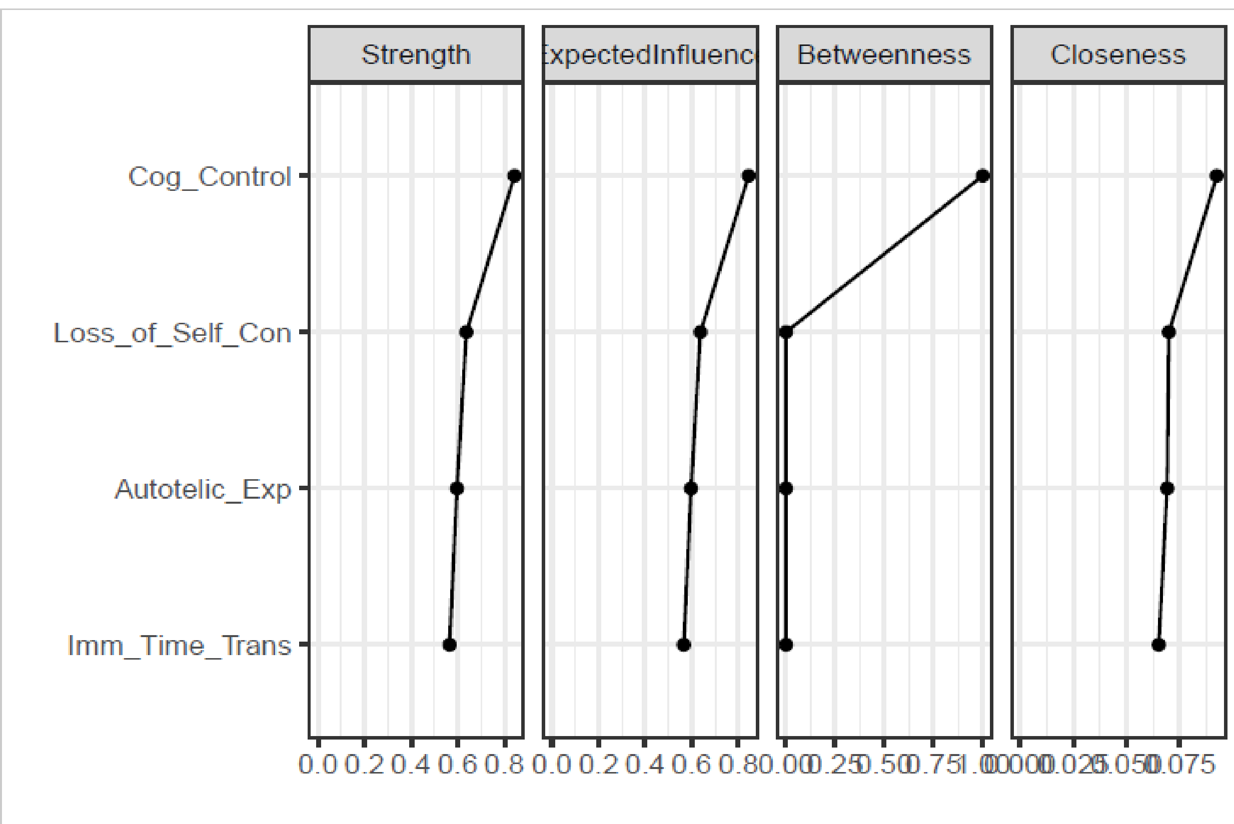

Fig.5: Strength, Expected Influence, Betweenness and Closeness Centrality Indices Plots of the Nodes of Cognitive Absorption Model based Science Academic Flow Scale

The node cognitive control is the strongest node of the network, followed by the nodes of loss of self-consciousness, autotelic experience and, immersion and time transformation. Closeness wise also, this node is vital, along with expected influence and betweenness.

Table 7: Node Centrality Indices Estimates

	Betweenness	Closeness	Strength	Expected Influence
Cog_control	1	0.09	0.843	0.843
Imm_Time_Trans	0	0.065	0.565	0.565
Loss_of_Self_Con	0	0.069	0.636	0.636
Autotelic_Exp	0	0.06904	0.596	0.596

Estimation of the Accuracy of the Edges of Cognitive Absorption Model based Science Academic Flow Scale Network Structure:

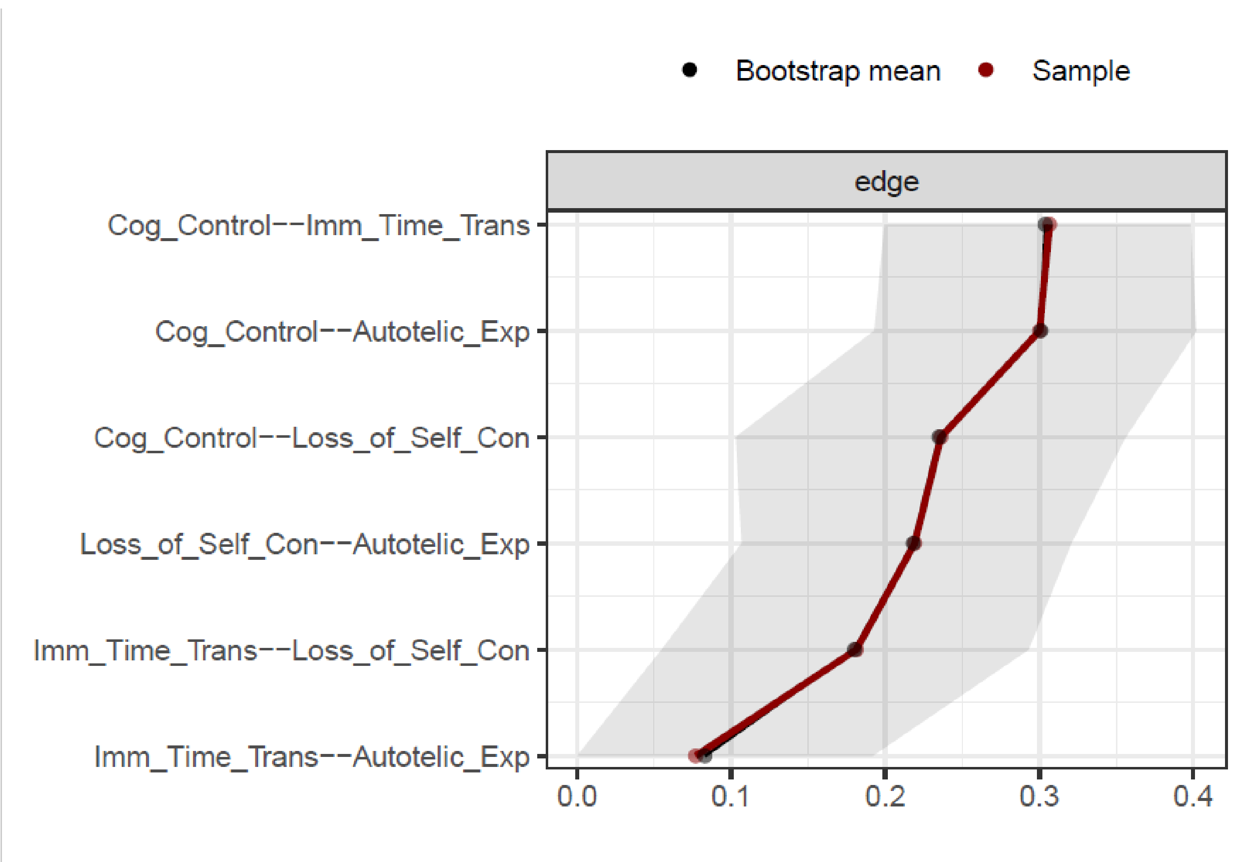

Fig.6: Estimation of Edge Weight Accuracy Non-Parametric Bootstrapped Confidence Interval Plot of Cognitive Absorption Model based Science Academic Flow Scale Network Structure

The non-parametric bootstrapped confidence interval is estimated for determining the accuracy of the edge weights with 95 % confidence considering the ordinal data measurement level in the present study (Epskamp, Borsboom and Fried, 2018). The above figure is generated after running the bootstrap technique for 500 times and on the allocation of eight processor cores. The edge weights of the network are represented by red dots and the grey region represents the 95 % confidence interval (CI) around them. In general, lesser number of nodes and larger sample size lead to the generation of smaller and non-overlapping CIs around the edges, which make the estimation more reliable and allowing mutual comparison, like the present study CI being in and around 0.1. The edge connecting the nodes cognitive control and Immersion Time and Transformation, is the strongest edge, and edge connecting nodes Immersion Time and Transformation, and autotelic experience is the weakest edge of the network, which can be true in 95% cases.

Estimation of Stability of the Edges of Cognitive Absorption Model based Science Academic Flow Scale Network Structure

Estimation of edge-weight accuracy using confidence interval is mostly difficult to interpret, and hence the stability of the edges, with respect to all the four centrality indices, are conducted by estimating the correlation of these metrics in original sample and in successively reduced cases through bootstrap replication.

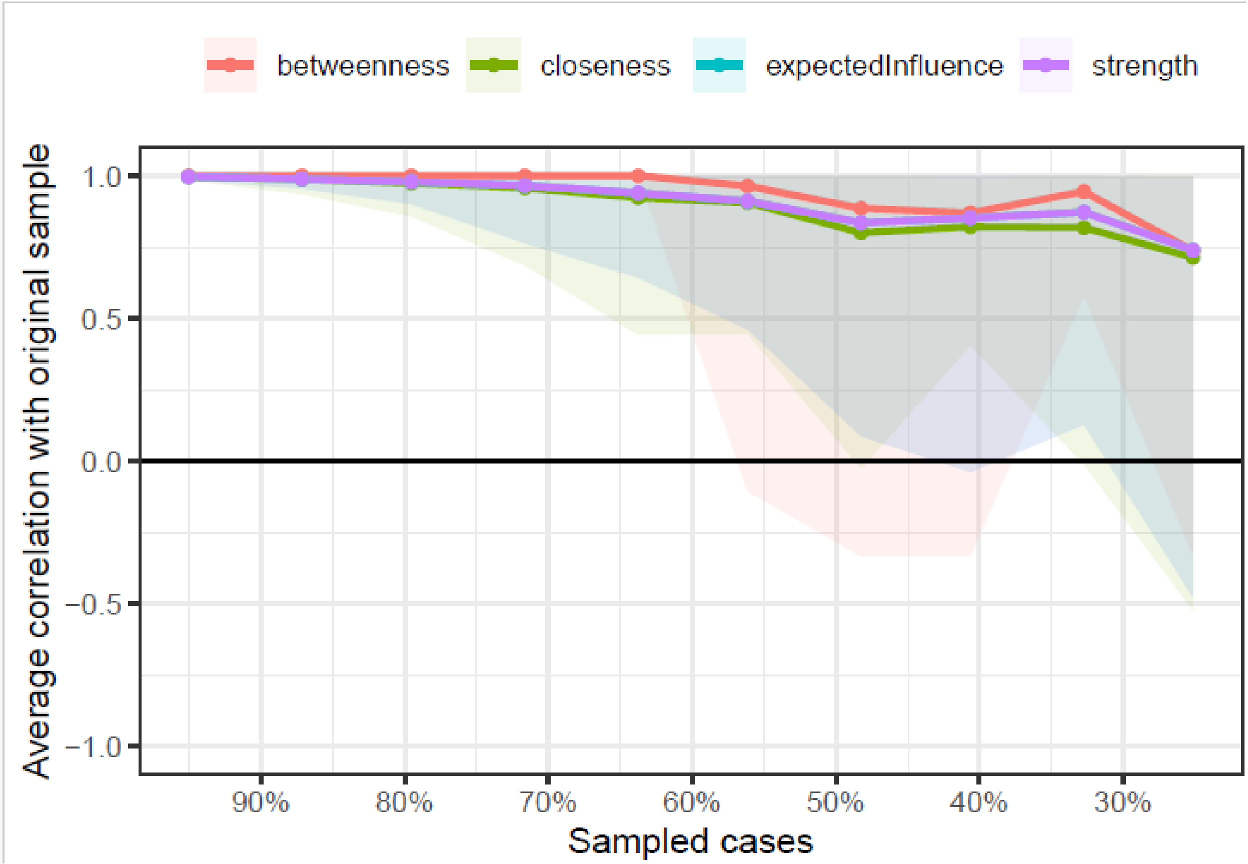

Fig.7: Estimation of Stability of Edges of Cognitive Absorption Model based Science Academic Flow Scale Network Structure with respect the Centrality Indices

The correlation stability CS coefficient quantitatively obtained is low at 0.363 than the benchmark of 0.5 but above the minimum value of CS coefficient at 0.25 (Epskamp, Borsboom and Fried, 2018).

Estimation of Bootstrapped Difference Test with respect to Nodes:

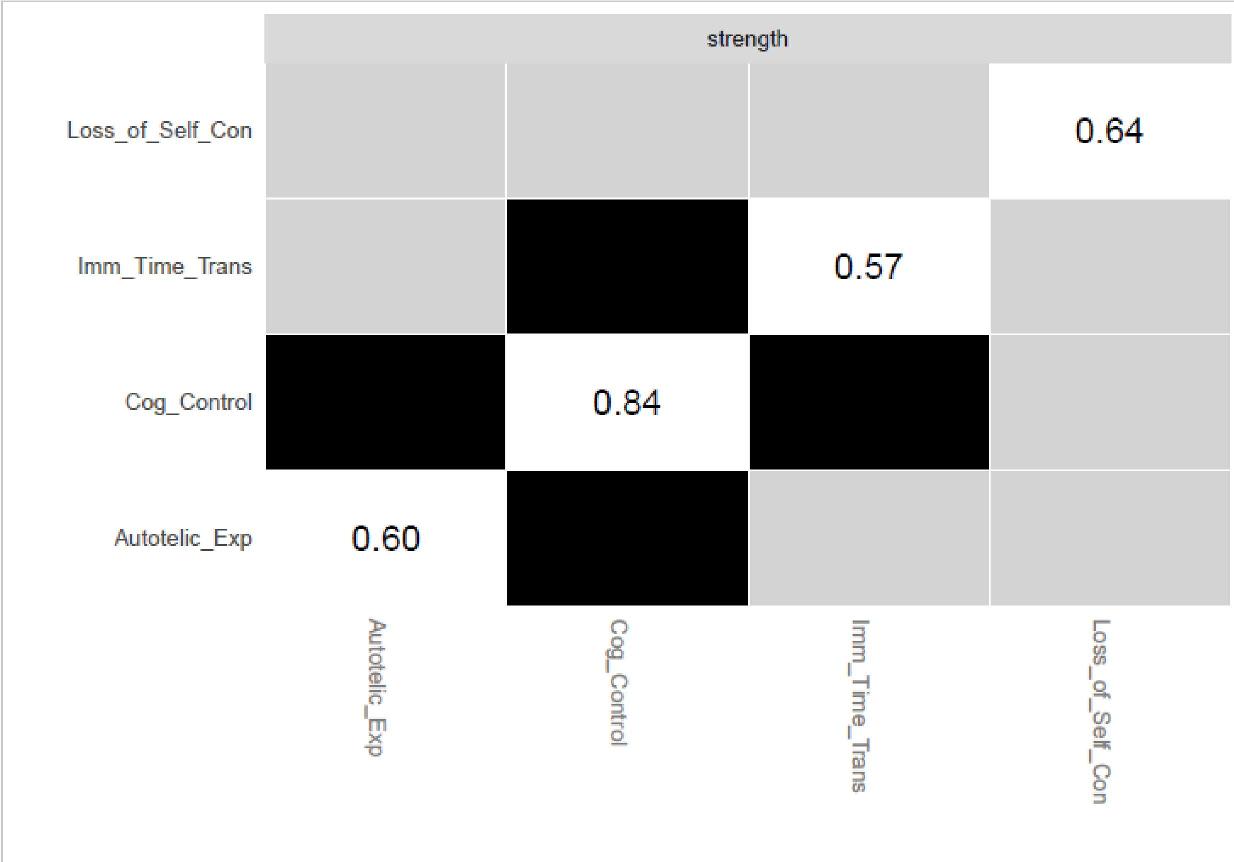

Fig.8: Bootstrapped difference tests (α = 0.05) between nodes of Cognitive Absorption Model based Science Academic Flow Scale Network Structure. Nodes which do not differ significantly from each other are represented by gray boxes in the plot. The significant ones are represented by the black boxes.

Estimation of Bootstrapped Difference Test with respect to Edges:

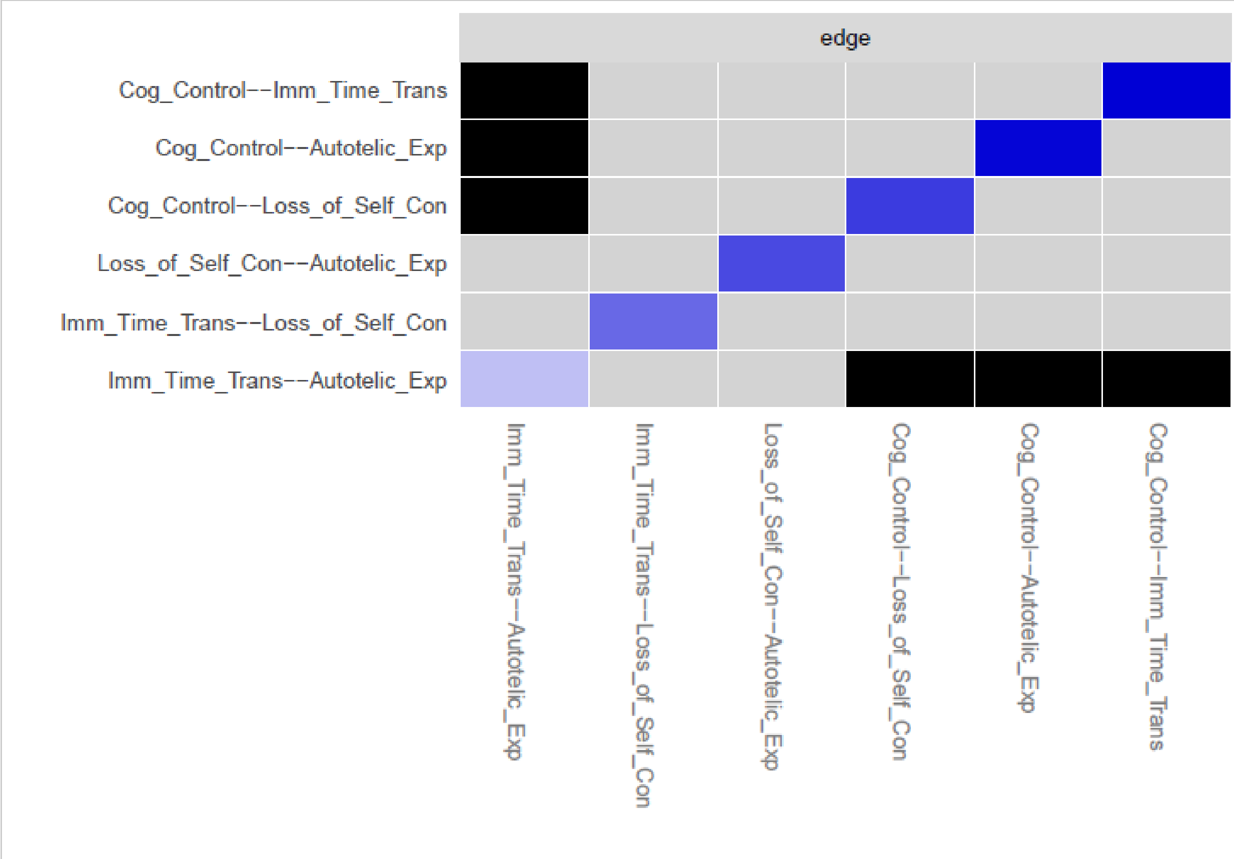

Fig.9: Bootstrapped difference tests (α = 0.05) between non-zero edgeweights and node strength of the Cognitive Absorption Model based Science Academic Flow Scale Network Structure. Edges which do not differ significantly from each other are represented by gray boxes in the plot. The significant ones are represented by the black boxes. Blue colored boxes represent the order of the edge-weights as displayed in figure 5 above.

Estimation of Structural Consistency of the Cognitive Absorption Model based Science Academic Flow Scale Network Structure:

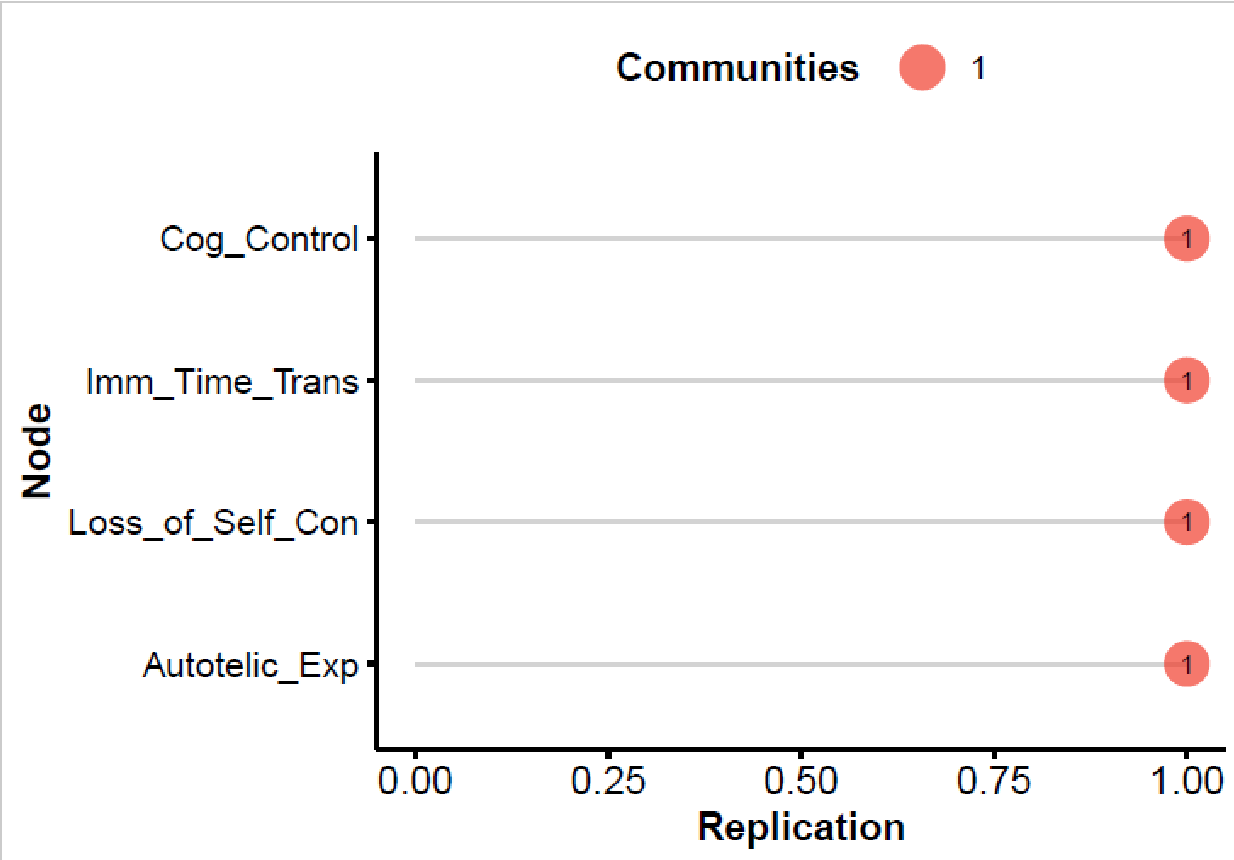

Fig.10: Structural Consistency Plot of Cognitive Absorption Model based Science Academic Flow Scale Network Structure

All the nodes load on same science academic flow network 100% when their consistency is tested through the replication of their original structure in multiple bootstrap-based samples, displaying very strong internal consistency. Quantitatively, the structural consistency of both the network and its individual nodes are obtained to be 1.

Discussion:

The present study adopted the novel network approach to validate the Cognitive absorption model based network structure of the instrument to measure science academic flow in secondary school students of India. It intended to gain deeper insights into the inter-relationships dimensions of this construct would have within themselves, which is not otherwise obtained by administering the CB-SEM based confirmatory factor analysis, where rather a simplistic approach of linear relationships are represented through path diagram to exist among the latent construct, its latent dimensions and the manifest items measuring them (van Zyl, 2018).

Also, the true data type of the data obtained from survey questionnaire is ordinal and not interval as it is assumed. Hence, it becomes important to apply ordinal confirmatory factor analysis based on polychoric tetrachoric correlation on the obtained data, instead of applying the Pearson product moment correlation based, covariance based confirmatory factor analysis technique for verifying the factor structure of the construct or its network as it is described under the new approach of network psychometrics (Epskamp and Fried, 2018).

As shown by El-Mawas and Heutte (2019), the nodes and the clusters of the newly adapted science academic flow scale, did come together to form the EBIC glasso network comprising of cognitive absorption and autotelic experience clusters. The cognitive absorption cluster itself was made up of three other sub-clusters of cognitive control, immersion and time transformation, loss of self-consciousness. The goodness of fit estimates of ordinal confirmatory factor analysis did show robustness and hence the Cognitive absorption model of flow is validated in the science education context as well. The CS - coefficient of the network, strength-wise, is above the minimum benchmark of 0.25 indicating a stable network as compared to the CS- coefficients of closeness and betweenness. The edge-weight confidence interval graph which estimates the accuracy of the edges of the network, by arranging them in descending order of strength using bootstrap technique, also needs to be interpreted with caution since 95% C.I. represented as the grey area in figure 5 is wide enough for the six edges orderings. This indicates that edges in the network vary significantly in strength and might not contribute much in keeping the network consistently, as further supported by the figures 6,7 and 8. However, the nodes or the statements of the scale loaded every single time on bootstrap replication across samples on their respective clusters displaying internal consistency within their respective cluster and external consistency by not loading on any other cluster. Thus the network has optimal structural consistency with respect to its nodes.

Since the study is first of its kind as per the investigators, there are no precedencies of results to share presently in the Indian context. Further replication studies of validation of the new scale on the secondary school students of others parts of the country hence stands highly warranted, especially because of the cultural diversity of India and varying levels of quality of science education in the country.

Limitations:

The present study was conducted on students of varying academic performance level, to validate its construct and content validities. However, the experiencing of academic flow in science subjects can be relatively a less frequent phenomenon in sciences students and can be more frequently experienced by academically bright and high science self-efficacy students. It is hence very important to further extend and replicate the validity exercise of the present study to a specific population of students with high science self-efficacy to establish the ecological validity of the scale.

Conclusion:

The availability of instruments to measure novel science education variables, which are in turn based on psychologically solid theoretical underpinnings and validated through robust psychometric techniques to prove being culturally neutral, is quintessential for the progress of research in science education in India and across the world. Our present exercise is a meniscal enterprise in this direction, with a hope that the tool is accessed and vigorously tested by all the stakeholders of science education research in the country.

Ethics Statement:

This study was conducted in accordance with the ethical guidelines outlined by Lovely Professional University. This study was conducted in accordance with the ethical guidelines outlined by Lovely Professional University. Prior to data collection, ethical approval was obtained from the Institutional Ethics Committee of the university, under approval number EC/NEW/INST/2022/3110.

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Disclosure Statement:

The authors report there are no competing interests to declare.

Data availability statement:

The data will be provided by the authors on request.

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