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Research paper

Development of Science Delay of Gratification Scale (SDOGS): Novel Amalgamation of Automated Item Generation, Genetic Algorithm, Nash equilibrium and Network Approaches in Psychometrics

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Abstract

Delay of gratification is a critical variable of study in the context of self-regulated learning. A science domain-specific instrument to measure this variable was not found in the literature. A new five-point Likert scale to measure Science Delay of Gratification was developed, purified, validated, and tested for measurement invariance concerning gender and batch in 719 students (395 girls and 324 boys) studying in 9th and 10th classes and belonging to the secondary schools spread across six states of India. The initial pool of 35 items was developed using the neural network-based Automated Item Generation approach using ChatGPT version. 1.1.0, based on the Cognitive-Affective Personality System (CAPS) theory proposed by [43], covering its three dimensions (Cognitive, Affective, and Behavioral). A novel approach of fusing Genetic Algorithm and Nash equilibrium concepts was used to extract the final parsimonious version of the scale comprising 21 psychometrically optimal and purified items. Network Psychometrics was used for exploring and validating the network's structure. Its invariance concerning gender and batch was also tested through a network consistency estimation technique. Appropriate packages of the open-source R version 4.2.3 were used to conduct the statistical analysis. The estimates of the obtained uniclustered network suggest the scale is psychometrically robust and displays invariance in measurement concerning gender and batch of the secondary school students. Open-ended responses from the sample subjects about the scale provided positive feedback about it studied using word cloud and thematic analysis. Implications of the study are discussed.

Keywords: *Automated Item Generation; Genetic Algorithm; Nash Equilibrium; Network Psychometrics; Science Delay of Gratification; Secondary School Students.*

1. Introduction

STEM education is critical for the progress of developing societies. From a sociological perspective, science education, which is at the center of STEM education, rewards its learners with better personal income opportunities and social prestige upon joining the workforce. It serves as a means for social mobility for its learners universally. The students of STEM education on joining the labor force are considered as a premium human capital contributing directly to the gross domestic product of a nation [74]. Owing to these advantageous aspects of STEM education, governments all over the world are investing heavily in improving the quality of STEM education provided at the school level. However, there are several challenges in retaining the interest of the students in science subjects by the time they pass out from schools [66]. One of the powerful psychological traits that can be promoted among secondary school students from the developing societies to increase their interest in science subjects, and in STEM education in general, is the delay of gratification in the context of science.

In their seminal work on academic delay of gratification, [4] referred to the construct as "students' postponement of immediately available opportunities to satisfy impulses in favour of pursuing chosen important academic rewards or goals that are temporally remote but ostensibly more valuable". The construct's independent existence can be traced back to the work on delay of gratification by [37], and it is recognized as a hallmark trait of self-regulated learning in students [38]; [13]. Over the years, the unidimensional 10-item academic delay of gratification scale (ADOGS) developed by [5] to measure this construct, emerged as a gold standard and is valid across multiple cultures [1]. Owing to its importance in the literature of self-regulated learning phenomenon [64]; [67], the variable academic delay of gratification (ADOG) is also incorporated as a vital component in several quantitative education psychology models related to self-regulated learning strategies, along with other closely associated self-regulated learning variables [2];[3]. However, while most of these variables have a five-point Likert scale response pattern, the unique four-point response pattern of the ADOGS scale presents issues in the comparison of the total scores [16] and scale ordering [72].

Also, with time, the avenues that satisfy the gratification-related impulses of present-day secondary school students are ubiquitous, bordering on addiction, and easily accessible due to the rapid advancement in information and communication technology, leading to a decline in the delay of gratification ability in them [40]. Certain avenues of impulses experienced by the secondary school students of the present era originate from the constant use of digital devices like mobile, desktop/laptops, social media platforms like Meta, Instagram, or Snapchat, online gaming, fast food apps, short-form content, and from the eternal factor of undesirable peer influence [6]. The 10 items of the ADOGS scale, developed in 1996, do not address these new sources of instant gratification of the present era. Such societal issues and technological developments necessitate the construction of a new, robust and parsimonious tool to measure delay of gratification on a five point Likert scale, and specifically in the context of science education at secondary school level, which is strongly based on theory, invariant in the measurement of the construct in subjects belonging to multiple groups and preferably valid across multiple cultures.

To ensure comprehensiveness in the study of the variable and provide a strong theoretical underpinning, the generation of the pool of items of delay of gratification in science education context must be based on the behavioural indicators of a famous theory like the Cognitive-Affective Personality System (CAPS) proposed by [39], which describes the construct using a three dimensions (Cognitive, Affective and Behavioral) approach. This leading theory on delay of gratification posits that the behaviour of an individual is a consequence of the dynamic interaction between cognitive processes, affective responses, and behavioural/situational contexts in which the individual is present. Another theory of delay of gratification, worth mentioning in this context for the sake of comparison with CAPS, is the Hot/Cool-system framework proposed by [43]. This theory posits that there are sections of the brain, namely, the cool, cognitive, "know" system and the hot, emotional, "go" system. While the former is responsible for the display of delay of gratification through self-regulation and self-control, the latter causes the display of instant gratification.

Also, the traditional approach of psychological tool construction is costly, time-consuming, and 40% of the developed items are not found to be effective even though they are framed by the experts themselves [33]; [22]; [53]. To reduce human interventions and automate this exercise, coherent yet creative items of a psychological scale can be generated using the neural network-based Automated Item Generation approach (AIG) [75]; [23]; [21] using open-source software like ChatGPT Ver. 1.1.0. To attain such items, the prompt engineering parameters like Temperature, Nucleus-sampling top_p, Frequency penalty, Presence penalty, and Max_count_token are used. Temperature takes care of the balance between creativity and focus while phrasing the items. Nucleus-sampling ensures coherence or presence of relatable and known phrases in the items related to the construct. Repeated use of similar phrases is penalized by the Frequency penalty, and frequent use of the same words is penalized by the Presence penalty estimate. The length of the items is kept in check by the estimate Max_count_token.

Moreover, psychological scales can be essentially parsimonious [7] in length to strike a balance between model complexity and goodness of fit [69]; [45] apart from ensuring greater utility and ease of administration them. Conventionally, the technique of scale purification, defined as "the justified removal of items from multi-item scales" [73] is used for obtaining a parsimonious version of psychological scales, and is a recognized practice in empirical research across several disciplines [24]; [46]. It involves the identification of psychometrically weak performing items and removing them based on estimates like inter-item correlation for redundancy, internal consistency reliability, item cross loading in exploratory factor analysis (EFA), and item factor loading during confirmatory factor analysis (CFA) for validity-related considerations. However, the statistical criteria used during the removal of items through these estimates are heuristic [10]. The present study tried to employ the Nash equilibrium concept under Game theory [44] as a new approach to extract a parsimonious version of the instrument with the rationale and codes for the same generated by ChatGPT. In this approach, the selection of items with optimal psychometric performance capabilities can be considered the game. The items are the players in the game. Each item "selects" a state (either to remain or move out of the scale) that optimizes its psychometric contribution in the context of other items or players. All the items or the players compete to meet the benchmarks of multiple objective functions like reliability, inter-item correlation, and item loadings simultaneously to register their contribution. Under the Nash equilibrium framework, each item's optimal position (i.e., whether it should remain or be removed from the scale) is determined in consideration of other items, ultimately converging to an equilibrium where no single item could improve the overall objectives by unilaterally changing its inclusion state, statistically implemented using genetic algorithms optimization technique [60].

Moreover, the conventional approaches of exploratory factor analysis and confirmatory factor analysis assume the data type to be interval and use Pearson Product Moment correlation based covariance matrix and Maximum Likelihood (ML) estimator to extract the factors and validate their structure, which can fail during model convergence, sending a wrong signal of the model being incorrect. This is owing to the fact that the data obtained from questionnaires through survey method is of ordinal data type requiring polychoric correlation and estimators like weighted least square mean and variance adjusted (WLSMV) (Lei and Shiverdecker, 2019), for performing ordinal factor analysis [17]. Also, the entire conception of psychological constructs, their dimensions and items related to each other linearly representing a latent model is simplistic and has limitations [61]. Usage of network approach is proposed to study psychological phenomenon to address the shortcomings of latent variable modelling paradigm based psychological questionnaire construction [14]; [18]. To enhance the validity of the obtained network structure, its invariance across subjects of different groups can be shown to be robust enough through network comparison test [9]; [47]; [71] which is the latent variable model (LVM) equivalent of measurement invariance testing statistical technique. The present study was primarily conceived to address the above discussed psychometric concerns while developing a robust Science Delay of Gratification instrument for secondary school students.

2. Method

2.1. Sample

The rationale behind the selection of secondary school students as the sample subjects for this present study is that, according to the research studies conducted by [41]; [48]; [49], it is during this stage of secondary level school education, that there is a change in the academic delay of gratification capability in these students, owing to the onset of another closely related variable Future Time Perspective in them [50]. Also, there has been a decline in the students selecting science in their final years of secondary education [54], which seriously impacts the prospects of not just science education but also STEM education and the related career prospects, eventually affecting the economic prosperity of the country [51].

The total sample size comprised 852 secondary school students. Post multivariate outlier detection using the Mahalanobis distance [42] estimation technique, the final sample size was reduced to 719. There were 395 girls (54.93%) and 324 boys (45.06%). 353 students (49.09%) belonged to class 9, and 366 students (50.90%) belonged to class 10. The sample subjects belonged to the six Indian states of Punjab, Rajasthan, Orissa, West Bengal, Andhra Pradesh, and Madhya Pradesh. While Punjab is a state in the Northern part of the country, Rajasthan is a western Indian state. West Bengal and Orissa are located in the eastern part of the country. Andhra Pradesh is a southern state of India, and Madhya Pradesh is located in the centre of the country.

2.2. Sampling technique

Due to the inherent geographical diversity associated with the population in this study, a stratified random sampling technique was used to select the sample subjects and control the variability in the Science Delay of Gratification trait in them arising due to their area, culture, gender, and class levels. Initially, the population is divided into north, west, east, south, and central zones of the country, which are the first strata. Then, a particular state is randomly selected from the list of states from each zone, forming the second stratum. Then, a school is randomly selected from the range of schools located in each state, forming the third stratum. The class level and gender of the students studying in them form the fourth and five strata respectively. All the randomly selected sample subjects can be treated to be homogeneous at the stratum level owing to their common average age of 14.5 years. Even though stratified random sampling assumes a stratum to be homogeneous, there would be variability within it due to the unaccounted factors of regional diversity.

2.3. Sample size

The detailed characteristics of the final sample size of 719 subjects are shown below:

Table 1: Sample Size Characteristics

S. No.	State	Percentage Out of 719 Sample Subjects	Gender		Class	
			Male	Female	9th	10th
1	Andhra Pradesh	151 (21.00%)	88 (58.27%)	63 (41.72%)	68 (45.03%)	83 (54.96%)
2	Rajasthan	65 (9.04%)	48 (73.84 %)	17 (26.15%)	27 (41.53%)	38 (58.46%)
3	Punjab	111 (15.43 %)	15 (13.51 %)	96 (86.48 %)	64 (57.65 %)	47 (42.34%)
4	Orissa	57 (7.92 %)	14 (24.56 %)	43 (75.43%)	32 (56.14 %)	25 (43.85 %)
5	West Bengal	94 (13.07%)	45 (47.87 %)	49 (52.12 %)	48 (51.06%)	46 (48.93%)
6	Madhya Pradesh	241 (33.51 %)	114 (47.30%)	127 (52.69%)	114 (47.30%)	127 (52.69%)
7	Total	719 (100 %)	324	395	353	366

2.4. Designing the instrument

Table 2: Dimension-Wise Statements of the Science Delay of Gratification Scale's Pool of Autogenerated Psychological Items and their Status

S. No.	Item Statement	Dimension	Status of the Item
1	"I remind myself that finishing my science homework now will give me more free time to enjoy social media later."	Cognitive - - These items focus on how students' thought processes, beliefs, and perceptions influence their behaviour, especially about instant gratification.	Deleted
2	"When I'm tempted to check notifications during a science lesson, I focus on how staying attentive will help me grasp the subject better."		Deleted
3*	"I often convince myself to delay gaming time because I know completing my science assignments will improve my grades."		Retained
4*	"I mentally calculate how much more I will understand if I study science now instead of watching short videos."		Retained
5*	"I think about the long-term benefits of scoring well in science before deciding to delay my social media usage."		Retained
6*	"When tempted to browse online shopping sites, I tell myself that mastering a science topic is a more valuable reward."		Retained
7	"I remind myself that resisting the urge to play online games will lead to better performance on my science tests."		Deleted
8*	"Before opening a fast-food app during a study session, I consider the importance of finishing my science project first."		Retained
9*	"I delay checking entertainment apps, reminding myself that focusing on science will help me in the future."		Retained
10*	"I focus on how completing a science project on time will reduce my stress, which helps me ignore distractions like texting friends.		Retained
11	"I feel a sense of accomplishment when I resist the urge to use my phone during a science class."	Affective - - These items address the emotional responses that drive students to seek immediate rewards, such as anxiety, frustration, and excitement, and how these emotions impact their engagement with science.	Deleted
12	"When I complete my science homework before using social media, I feel relieved and proud."		Deleted
13*	"I manage my frustration with science projects by reminding myself how good it will feel to finish them before indulging in gaming."		Retained
14*	"Even when I feel anxious about missing social media updates, I focus on the pride I will feel after completing my science assignments."		Retained
15*	"I feel more motivated to study science when I manage my impatience and delay watching short entertainment videos."		Retained
16*	"I reduce my anxiety about schoolwork by reminding myself how much better I'll feel if I resist distractions and focus on science."		Retained
17*	"When I hold off on ordering food online during science study sessions, I feel more disciplined and in control."		Retained
18*	"I get a boost of confidence when I delay checking my phone until after finishing a science experiment."		Retained
19*	"Even though I get tempted to browse online shops, I feel more in control when I focus on completing my science assignments first."		Retained
20	"I feel less stressed about science homework when I resist the urge to use fast food apps or play video games during study time."		Deleted
21*	"I complete my science homework before checking Instagram or social media updates."	Behavioural / Situational - These items capture the observable behaviours students	Retained

22	"When studying science, I turn off notifications to avoid distractions from my phone."	engage in when faced with situations that offer instant gratification. They also reflect how students act in specific situations, like distractions from technology or the pressure of social media, and how they impact their science learning.	Deleted
23*	"I make sure to finish my science assignments before logging in to play online games”		Retained
24	"I often choose to study for science exams instead of browsing e-commerce sites or watching short videos."		Deleted
25	"I delay ordering food online until after completing my science homework."		Deleted
26*	"When working on a science project, I avoid distractions like YouTube or entertainment apps until I’m done."		Retained
27	"I make it a point to complete my science experiments before responding to friends’ messages."		Deleted
28*	"I stay focused on studying science, avoiding the temptation to check my phone for new notifications."		Retained
29	"I resist playing mobile games during science study sessions by reminding myself of how important it is to complete my work."		Deleted
30*	"When I feel tempted to take a break and use fast-food delivery apps, I remind myself to finish my science assignments first."		Retained
31*	"I often finish science tasks before watching reels or short clips online as a reward."		Retained
32	"I hold off on buying things online until after I’ve completed my science homework."		Deleted
33	"I wait to check social media trends until I’m done with my science projects."		Deleted
34	"I avoid watching short entertainment videos while studying science to maintain focus."		Deleted
35*	"When I have science work to do, I consciously stay away from peer-influenced activities like online trends until I finish."		Retained

Autogeneration of pool of psychological items comprised of 10 items under Cognitive dimension, 10 items under Affective dimension and 15 items under Behavioural / Situational dimension of Science Delay of Gratification generated as per the behavioural indicators of Cognitive Affective Personality systems CAPS theoretical model, using CHATGPT Ver.1.1.0. Prompt engineering parameters consisted of temperature 0.75, nucleus sampling top_p 0.8, frequency penalty 0.4, presence penalty 0.5 and max_count_token of 150 words. The responses of the subjects were to be recorded on a five-point Likert scale with 1 = Strongly Disagree and 5 = Strongly Agree.

2.5. Procedure

A Google form questionnaire was prepared to conduct the survey, consisting of the fields like state, gender, and class of the sample subjects, along with the 35 autogenerated items of the Science Delay of Gratification construct. At the end of the questionnaire, the participants were asked to share their feedback on the exercise as an open-ended question. Prior permission was taken from the head of the institution who allowed for the collection of data for the research on their campus. The link to the Google Form questionnaire was shared with the school authorities, who made the arrangements for the data collection during regular class sessions in the presence of the subject teachers. All ethics-related statements were incorporated along with the instructions given to the subjects in the first section of the questionnaire. It was also informed to the subjects in writing that their participation in filling out the questionnaire, after reading the instructions, would be deemed as involving their voluntary consent for the data collection exercise. The subjects took 30-40 minutes to complete responding to the questionnaire and submit the form electronically.

3. Results

3.1. Scale purification using a fusion of genetic algorithm and Nash equilibrium

The 35 items of the Science Delay of Gratification scale were subjected to Nash equilibrium-based scale purification using a genetic algorithm optimization approach to obtain seven items from each of the cognitive, affective, and behavioural/situational dimensions of the construct. To integrate Nash Equilibrium as an objective function into the Genetic Algorithm (GA) for purifying the scale, the optimization process was framed in a way that each decision of selecting an item was treated as a "strategy" in a multi-agent game. The equilibrium was reached when no “agent” or selected item benefited from changing its decision of selection unilaterally, given the decisions of others. In this way, the items of the scale acted as players, the decision to either delete or retain the items was the strategy, and high internal consistency (reliability) and factor loading (validity), coupled with low redundancy of items, represented the “pay-off or utility”. For Nash Equilibrium, the best response for each selected item by maximizing overall reliability and validity, while minimizing redundancy, was considered. This psychometric balance acted as a multi-objective optimization function. A block diagram to represent the adopted framework in a simplified manner is presented below:

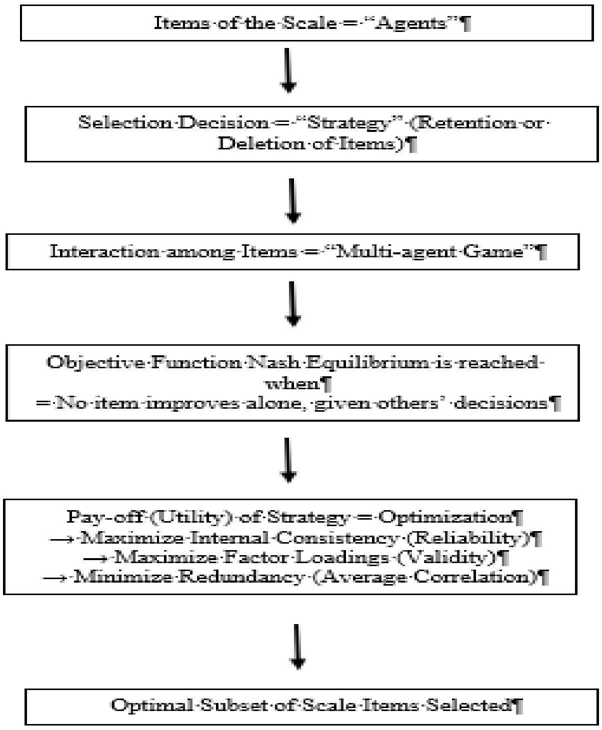

Fig. 1: Block Diagram of Genetic Algorithm Framework Using Nash Equilibrium as Objective Function for Science Delay of Gratification Scale Purification.

The codes were developed by ChatGPT, and they were run on the interface of RStudio, an open-source software to obtain the results shown below:

Table 3: Dimension-wise Retained Items of the Final Scale of Science Delay of Gratification

S. No.	Dimension	Retained Items	Objective Functions Reliability through Cronbach's Alpha	Validity Score through Factor Loadings	Redundancy through Average Correlation
1	Cognitive	3,4,5,6,8,9,10	0.874	0.704	0.5
2	Affective	13, 14, 15, 16, 17, 18, 19	0.904	0.756	0.575
3	Behavioural/ Situational	21,23, 26, 28, 30, 31, 35	0.906	0.765	0.581
Note:	The statement of all the 21 retained items is shown in bold and italics in Table 2, with an asterisk mark on their serial number.				

As part of the scale purification exercise using genetic algorithm and Nash equilibrium concepts together, if an item is part of an equilibrium set, its inclusion should not make the alpha or validity estimate worse, while ensuring the redundancy estimate is minimized. Apart from the ChatGPT-generated code to conduct the scale purification exercise [55] required the installation and activation of two of its packages, namely GA [59] and psych [56], for the successful extraction of the purified and retained items of the parsimonious Science Delay of Gratification scale.

3.2. Network approach based exploratory graph analysis (EGA)

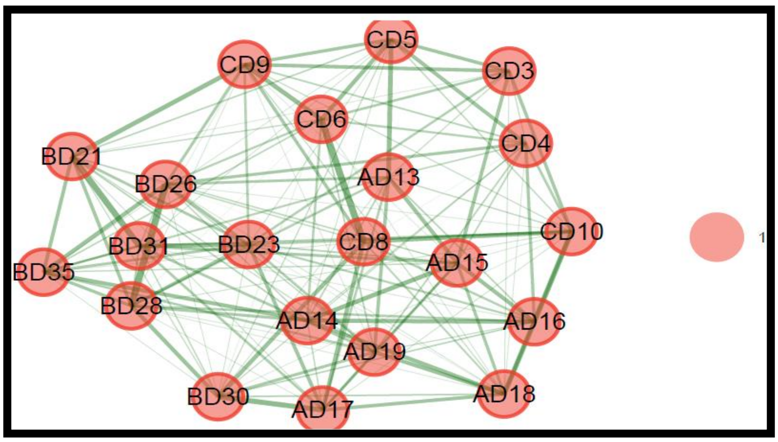

Fig. 2: Network Structure of Science Delay of Gratification Scale.

To identify the underlying structure of the empirical data, the exploratory graph analysis (EGA) technique makes use of the Gaussian Graphical Model (GGM) network estimation method, where the partial correlations among items represent the network edges, and the clusters of items or nodes (factors) are identified through the Walktrap community detection algorithm. The algorithm is based on the simple idea that if certain nodes are very closely knitted to each other, a random walk on the paths or edges connecting them would start from one node and every time end at another closely connected node. A group of such nodes is identified, leading to the formation of a cluster. The EGA technique revealed a single cluster network structure of Science Delay of Gratification, with all its 21 nodes connected through edges or connections of varying strengths, representing one unique ecosystem of its own in totality [15]. The task was conducted using the R package EGAnet [25].

Estimation of Structural Consistency of the Science Delay of Gratification Network:

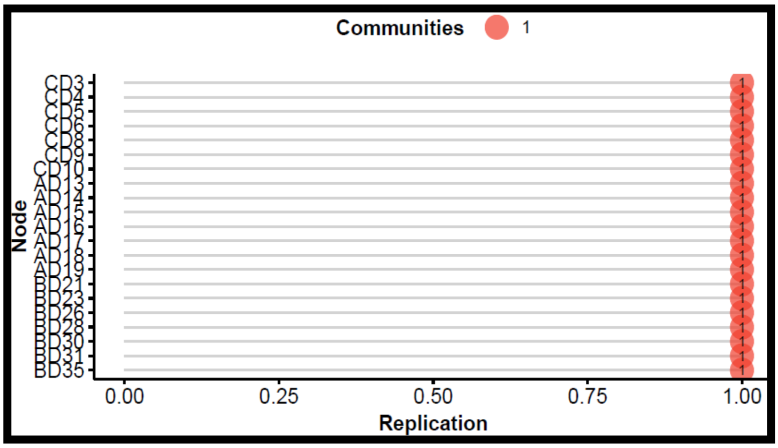

Fig. 3: Structural Consistency of Science Delay of Gratification Network.

To ensure that the obtained network structure is not sample-dependent, but can remain stable and be reproduced in other samples, its structural consistency was estimated using a bootstrapping technique for 500 runs on a sample size of 719 secondary school students. All 21 nodes loaded each time on the Science Delay of Gratification cluster without showing any tendency for a split in the 500 repeatedly resampled data sets. The structural consistency index of 1 of the network quantitatively reflected the same result. The task was conducted using the R package bootnet [17].

Estimation of Node Predictability of Science Delay of Gratification Network

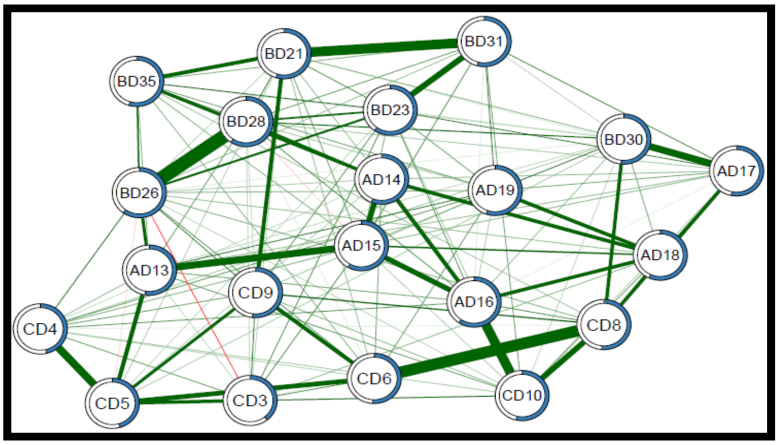

Fig. 4: Node Predictability of Science Delay of Gratification Network.

Table 4: Node Wise Predictability Estimates of Science Delay of Gratification Network

S. No.	Node	R^2
1	CD3	0.391
2	CD4	0.462
3	CD5	0.454
4	CD6	0.511
5	CD8	0.513
6	CD9	0.519
7	CD10	0.537
8	AD13	0.527
9	AD14	0.563
10	AD15	0.584
11	AD16	0.595
12	AD17	0.533
13	AD18	0.569
14	AD19	0.555
15	BD21	0.548
16	BD23	0.6
17	BD26	0.602
18	BD28	0.596
19	BD30	0.518
20	BD31	0.542
21	BD35	0.547

Node predictability indicates the proportion of variance or change in a node that can be explained by the other interconnected nodes of the network. For the node BD26 with a high predictability estimate R2 at 0.602, it implies that nearly 60.2 of % change in this node can be explained by the other nodes to which it is connected in the network. The same estimate for the node CD3 is the lowest in the network at 0.391, which implies that only 39.1 of % variance in this node can be explained by the nodes to which it is connected in the Science Delay of Gratification network. Overall, all the nodes have fairly robust predictability estimates, suggesting that all the nodes in the network represent part of one cohesive cluster. The task was conducted using the R packages mgm [26] and qgraph [20].
Estimation of Network Loadings and Goodness of Fit:

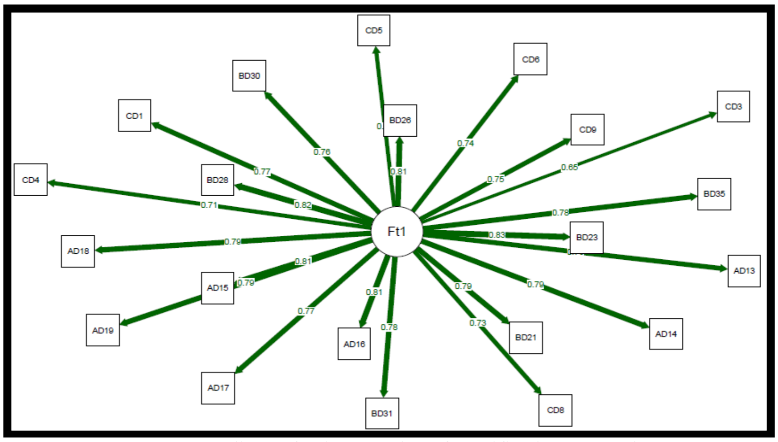

Fig. 5: Loadings of Science Delay of Gratification Network.

An ordinal CFA was conducted on a dataset of 719 sample size. Since the hypothesized single cluster tool of Science Delay of Gratification has its items' responses obtained from a five-point Likert scale, the data type is ordinal in nature, hence requiring the use of the Weighted Least Square Mean and Variance (WLSMV) estimator to provide robust estimates for fit indices and factor loadings. It does so by adjusting for the non-normality and unequal variances inherent in categorical responses. The goodness of fit estimates obtained were shown below:

Table 5: Goodness of Fit Estimates of the Network

Estimand	CFI	TLI	SRMR	RMSEA	CFI. Robust	TLI. Robust	SRMR_ Bentler	RMSEA. Robust
Benchmark	>0.95	>0.95	<0.08	<0.06	>0.95	>0.95	<0.08	<0.06
Estimate	0.999	0.998	0.032	0.034	0.941	0.934	0.028	0.072
Remarks	Excellent	Excellent	Excellent	Excellent	Good	Good	Excellent	Good

The fit indices suggest that the hypothesized single-dimensional model of the Science Delay of Gratification construct provides a good fit to the data, with all estimates exceeding or being close to the recommended benchmarks [27]. The loadings are also robust enough, ranging from 0.65 for the node CD3 to 0.83 for the node BD23. Hence, the ordinal CFA with the WLSMV estimator supports the single cluster network structure of the Science Delay of Gratification scale, with all model fit indices indicating a good model fit to the data.
Estimation of the Regularized Network Structure:

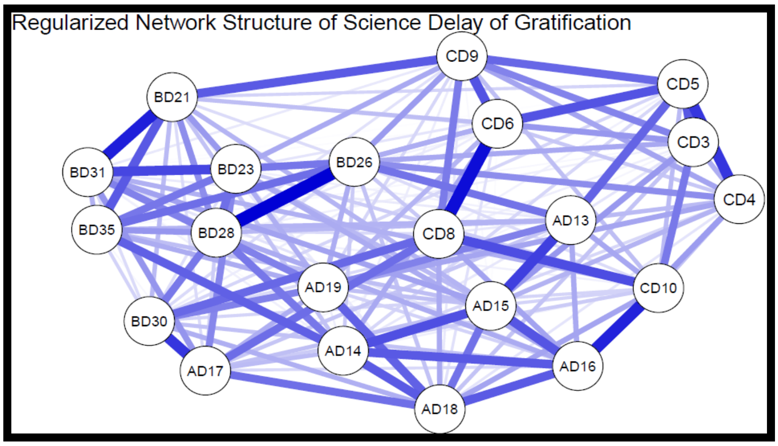

Fig. 6: Regularized Network Structure of Science Delay of Gratification.

To reduce the existence of spurious edges in the Science Delay of Gratification network, a regularization technique called the least absolute shrinkage and selection operator (LASSO) was used, which reduced the correlation coefficient of any spurious edges in the network to exactly zero. This resulted in obtaining a clutter-free network with the most prominent edges to represent, a network which is easily interpretable and extendable to other samples, using a tuning parameter λ. The LASSO produces networks with nodes completely connected, to a network with zero connectivity among nodes, for varying values of the tuning parameter. The best network from the lot is selected by estimating the Extended Bayesian Information Criterion (EBIC) for each network and settling with the one that has the minimum EBIC estimate.
Estimation of Centrality Indices of the Network Nodes:

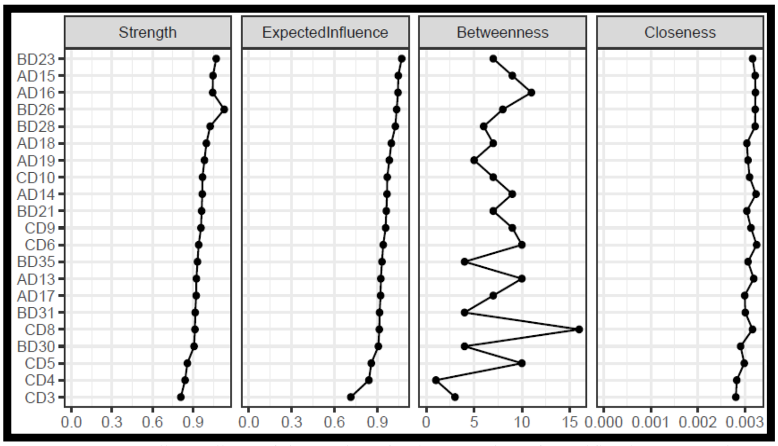

Fig. 7: Centrality Indices of the Nodes of Science Delay of Gratification Network.

Strength-wise, the most important node of the network is BD23 owing to its direct connectivity to several other nodes of the network, followed by AD15 and AD16. CD3 is the weakest node of the network. These nodes have a critical role to play in binding the entire network together; their respective behavioural indicators are gateways to promote Science Delay of Gratification in secondary school students. Additionally, CD8 is the most important node related to other nodes of the network indirectly, and CD4 is the least indirectly connected node of the network. All nodes of the network are, on average, in relatively proximity to each other, representing a cohesive cluster.

Estimation of the Edge-Weight Accuracy:

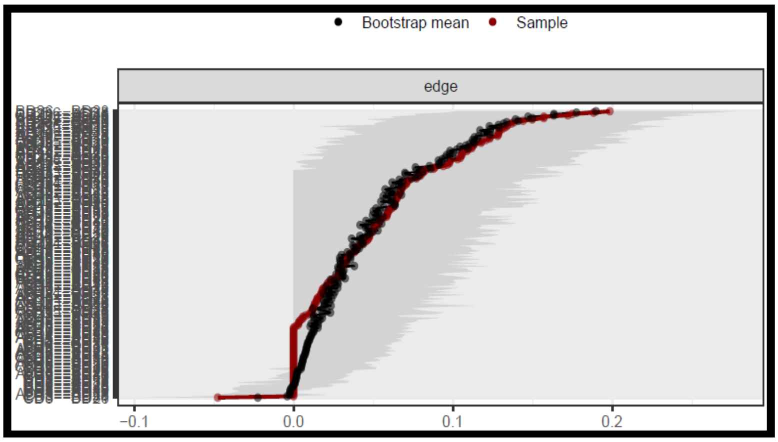

Fig. 8: Confidence Interval Estimation of the Edge-Weights Accuracy of the Science Delay of Gratification Network.

The order of the edges of the network in descending order of their strength, as obtained from the empirical data, is compared to ensure the stability of the network through a search for its existence in 500 sample groups replicated through a bootstrapping technique. Estimation of Confidence intervals around the edge weights indicates the precision and stability of the overall network. Since zero falls within the lower and upper bounds of the confidence interval (-0.1, 0.2), the strength of the relationship between the nodes in the Science Delay of Gratification network is uncertain and may be close to zero. This means the two nodes may not be reliably associated in the population, even if they appear connected in the sample data of 712 secondary school students.

Estimation of Correlation Stability (CS) Coefficient of the Network

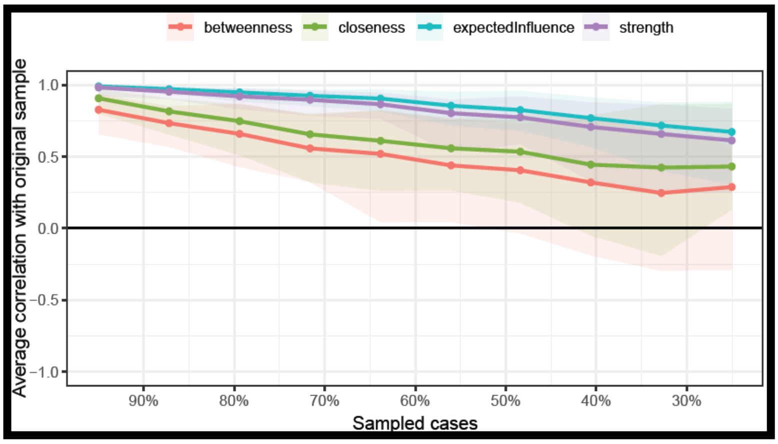

Fig. 9: Correlation Stability Plot of the Science Delay of Gratification Network.

The correlation of the network structure obtained from the complete sample size of 719 subjects and the network structures obtained by successively reducing the sample cases is estimated to figure out the minimum sample size at which a stable network emerges and continues to

remain the same for higher sample sizes. The lower the number of sample cases required to form a stable network, the more reliable it is. The concept is quantitatively expressed through the CS-coefficient, which for the present network stands at 0.439, above the minimum benchmark of 0.25 [19].
Estimation of Edge Weights Difference Plot of the Science Delay of Gratification Network:

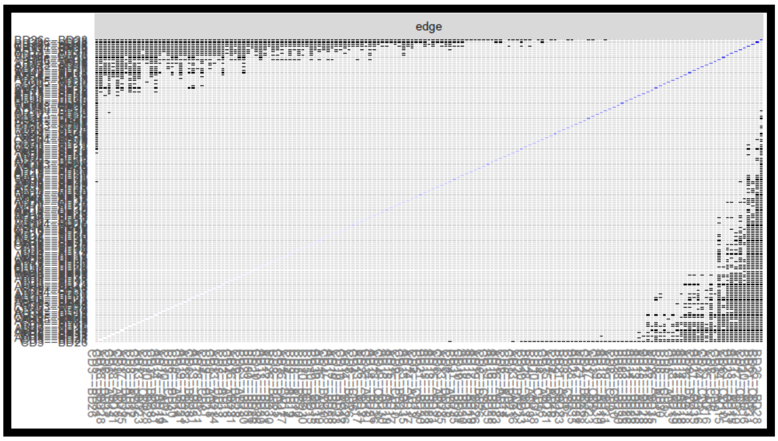

Fig. 10: Edge Weights Difference Plot of the Science Delay of Gratification Network.

The plot of edge weight differences comprises grey, black, and blue boxes. All the edge weight differences represented by grey boxes are non-significant ones, requiring no further analysis. The edge-weight differences represented by black boxes stand for significant relationships existing between their corresponding nodes and are consequential with respect to arriving at any inference pertaining to the stability, accuracy, and replicability of the network in further studies. The blue boxes represent relationships that are of potential significance but require further verification in the future. The task was conducted using the R package psychTools [57].
Estimation of Nodes Difference Plot of the Science Delay of Gratification Network:

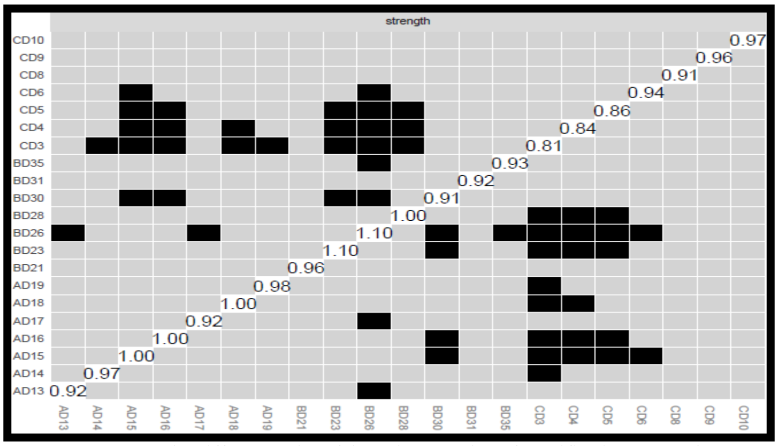

Fig. 11: Node Difference Plot of the Science Delay of Gratification Network.

Black boxes indicate the core nodes that impact the network structure or the trait of Science Delay of Gratification and have high external validity. Grey boxes generally indicate that differences between node centrality values, like the strength of the nodes, are not statistically significant, and hence cannot be extended to replicate in other sample groups or contexts.

3.3. Estimation of independent groups' Gaussian network comparison test concerning gender

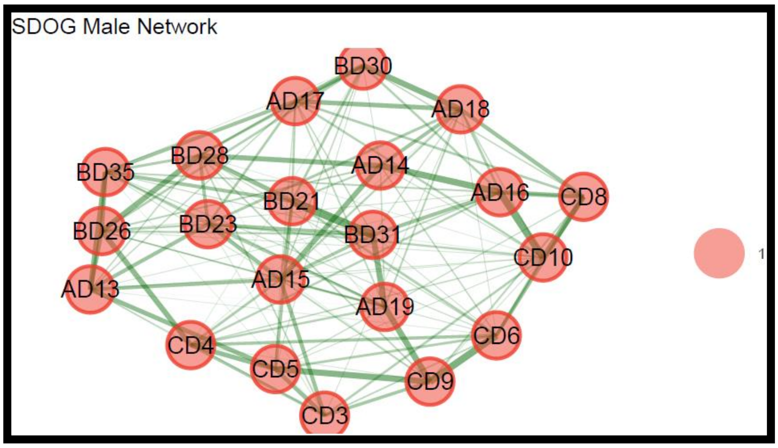

Fig. 12: Network Structure of Science Delay of Gratification Scale in Male Secondary School Students.

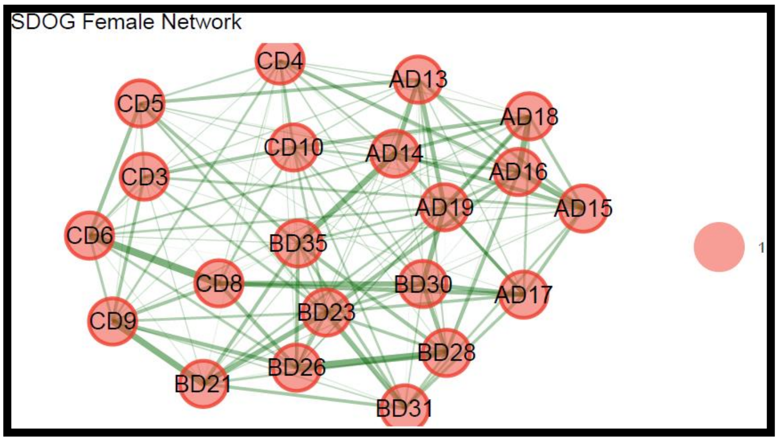

Fig. 13: Network Structure of Science Delay of Gratification Scale in Female Secondary School Students.

The network structure invariance test was conducted to obtain the estimated test statistics M at 0.193 for a p-value 0.594, which is greater than the level of significance of 0.05, representing a non-significant result. It implies that the overall structure of the two networks of Science Delay of Gratification in male and female students in terms of the patterns of edges connecting the nodes is not significantly different. The global strength invariance test assesses whether the overall connectivity of the network, composed of the sum of all edge weights, differs significantly or remains indistinguishable between the two networks. Science Delay of Gratification in male and female students. The global strength estimates per group were 9.982 and 9.989, respectively, with the test statistic S = 0.00617 for a p-value = 1, which is greater than the level of significance of 0.05, representing a non-significant result. It implies that the overall network connectivity is similar in both groups. The same psychological items used to measure Science Delay of Gratification in male students can be used to measure the trait in female students as well. The task was conducted using the R package networkcomparisontest [70].

Estimation of Independent Groups Gaussian Network Comparison Test concerning Class

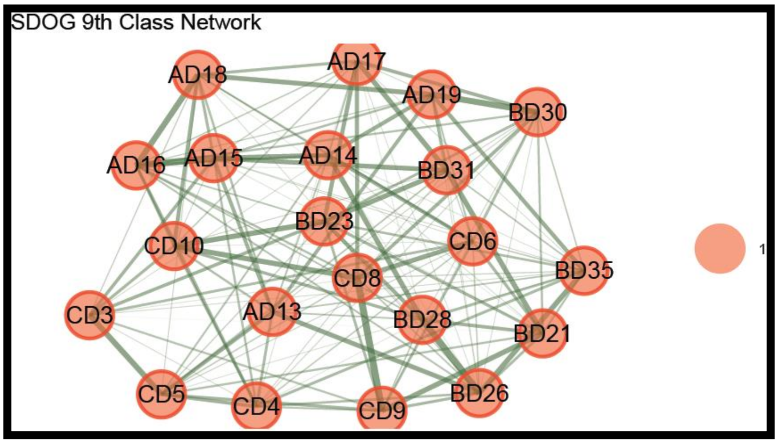

Fig. 14: Network Structure of Science Delay of Gratification Scale in 9th Class Secondary School Students.

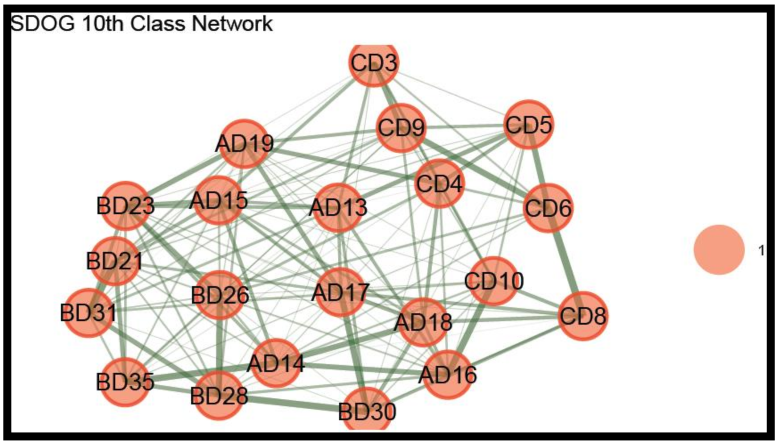

Fig. 15: Network Structure of Science Delay of Gratification Scale in 10th Class Secondary School Students.

The network structure invariance test was conducted to obtain the estimated test statistics M at 0.208 for a p-value 0.465, which is greater than the level of significance of 0.05, representing a non-significant result. It implies that the overall structure of the two networks of Science Delay of Gratification in 9th and 10th class students in terms of the patterns of edges connecting the nodes is not significantly different. The global strength invariance test assesses whether the overall connectivity of the network, composed of the sum of all edge weights, differs significantly or remains indistinguishable between the two networks of Science Delay of Gratification in 9th and 10th class students. The global strength estimates per group were 9.915 and 10.015, respectively, with the test statistic S = 0.1009 for a p-value = 0.475, which is greater than the level of significance of 0.05, representing a non-significant result. It implies that the overall network connectivity is similar in both groups. The same psychological items used to measure Science Delay of Gratification in 9th class students can be used to measure the trait in 10th class students as well.

3.4. Analysis of the qualitative feedback using word cloud generation and thematic analysis

Fig. 16: Word Cloud of the Feedback received from Science Delay of Gratification Scale Administration on Secondary School Students.

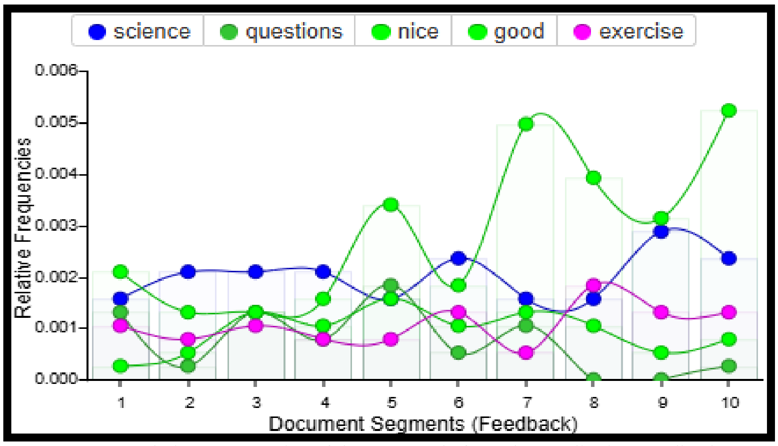

Fig. 17: Relative Frequencies of the Keywords from the Qualitative Feedback.

The questionnaire used to collect the responses of the scale's item had an open ended question at the end where the participants were asked to provide their feedback on the exercise as an open ended question. After removing the inconsequential responses to this question, the leftover textual context was subjected to qualitative analysis by generating the word cloud graphical representation and developing a graph of the most important keywords emerging from the document using the online open-source web tool Voyant Tools [62]. There were 3,828 total words in the uploaded document, with 721 unique words. The vocabulary density was 0.188. The readability index was 9.234. The average words per sentence were 28.4, and the most frequent words with their count of occurrence were good (110), science (77), exercise (41), nice (36), and questions (28). The general inference arrived from the qualitative analysis of the feedback was that the students liked the nice exercise of collecting their responses to good questions pertaining to an important science education variable, like delay of gratification.

A thematic analysis of the feedback obtained from the students, conducted using the online platform AILYZE, revealed the following themes and their sub-themes:

Table 6: Thematic Analysis of the Feedback obtained for Science Delay of Gratification Scale

S. No.	Theme	Sub-themes
1	Impact of the Exercise on Student Self-Awareness and Motivation	Realization of personal study habits and distractions Increased motivation and determination to focus on studies Reflection on mistakes and need for improvement Recognition of the importance of science and academics
2	Feedback on Survey Design and Content	Repetitiveness of questions causes boredom Suggestions for the inclusion of other subjects besides science Relevance of questions to daily life and student experiences Perceived pressure and stress related to study workload
3	Role of Distractions and Time Management in Study Practices	Impact of social media, mobile phone use, and gaming on focus Strategies to avoid distractions and prioritize study tasks Balance between study and breaks or self-care Awareness of managing time effectively for academic success

The analysis revealed three major themes related to the usefulness of the data collection exercise of the scale on students' self awareness and motivation, very important feedback on the content of the scale and and the survey design of the research, and on the impact of present day distractions and role of time management in study practices as realized by the students themselves while filling the questionnaire. In particular, the thematic analysis revealed, several sub-themes like the importance of science as an important subject, realization of poor study habits and distractions experienced while studying like social media, games and mobile phones, recognizing mistakes and resolving to correct them, suggestions to include not only science but also other school subjects in the scale, balancing study and self care, using available time very effectively, pressure experienced while studying science, relatedness of the items with the daily life instances and also repeatitiveness of certain items leading to boredom towards the exercise. Overall, the thematic analysis revealed the usefulness of the exercise of collecting data for the Science Delay of Gratification scale in its entirety.

4. Discussion

4.1. Educational realities of science education in the Indian schools

The advantages of studying science at the secondary level of school education on future job prospects were explored by [29]. The study reported that in comparison to humanities and business disciplines, students studying science at the secondary school level have 22% more chances of earning a higher salary in the future, which is further improved if the fluency of these students while conversing in English is good. These students also have higher chances of completing their graduation, working in the public sector, and also making their foray into entrepreneurship. However, the very textbooks which make up the main source of learning science in school education, present the subject in a rather simplistic and reductionist way, without paying any attention to the aspects of developing a conception of science as a subject of utility by the students, its process skills and constructivist approach based thinking structure and the cultural and contextual dimensions while learning it [30].

4.2. Application of the present research on educational practice in developing societies like India

The conception of learning or the epistemological beliefs a student holds for science is closely related to a host of other self-regulated learning beliefs like task-value, self-efficacy, and goal-orientation [63]. It is important that secondary school students be trained to develop self-regulatory capabilities by offering them quality science education in 9th and 10th classes, so that these students become lifelong learners of science [68]. Science Delay of Gratification, as an academic variable, is vital for the promotion of self-regulatory capabilities in learners [11]. The availability of a valid, parsimonious, and measurement-invariant tool to assess this trait, developed in an economical manner using an automated item generation approach, can catalyse multiple and quality research studies by the research scholars, researchers, and practitioners of science education, especially in developing Indian societies.

4.3. Implications of the present research on educational theory and practice

According to neuroscience, the brain of adolescent students is not mature enough, until early thirties [65], to show restraint or control over impulses and urges of seeking sensation or risks which increase during this development stage. However, when the adolescents, transiting from childhood to adulthood, indulging in high risk taking, sensation seeking or any other means of instant gratification, are instructed about the potential adverse consequences in future for doing so, they are found to display higher levels of delay of gratification owing to a change in their future time related perspectives [58]. One possible explanation behind the working of this mechanism can be explained by the loss aversion concept of Prospect theory by [31], which states that, psychologically, the pain of any loss is nearly twice as powerful as the pleasure of gaining any reward or gratification, or "losses loom larger than gains". Based on this theoretical underpinning, practitioners of science education can design their curriculum effectively towards the promotion of delay of gratification in secondary school students who are born digital natives [52]. They must be taught science using digital devices following just-in-time teaching and learning strategies, where the classes are activity-based, customized to the learning needs of the learners [32], and culturally embedded so that they appreciate the purpose and utility of attending science classes. Such a development might change the perception of these students towards digital devices and gadgets, from being the source of instant gratification to being potent learning resources for science education.

4.4. Future possibilities of research for science education researchers and science educators

The variable delay of gratification is culturally sensitive by nature [8], and so is science education [12]. Hence, it becomes imperative that the newly developed tool's psychometric properties and measurement invariance capabilities across the groups of gender and class, be tested on secondary school students studying science and belonging to multiple cultures. Differential item functioning (DIF) analysis of the items of this scale with respect to cultural groups can be conducted to check for the invariance in the response pattern for items by students with equal measures of delay of gratification in science but belonging to different cultures [28]. Also, future studies can conduct Latent profile analysis (LPA) [34] to extract categories of homogeneous groups of subjects based on their scores of delay of gratification in science. Such an important statistical exercise can aid in the development of customized interventions to promote this trait and self-regulated learning capabilities in general in secondary school students. Owing to the strong relationship existing between delay of gratification and future time perspective, an exercise to construct a robust and parsimonious tool to measure the latter trait in the science education context can be taken by researchers. A limitation of the present study has been that the auto-generated psychological items were not vetted by subject matter experts, and their content validity index [35] remains to be estimated in future studies [33]. Also, the present scale is developed as a measure to estimate the delay of gratification in secondary school students, specifically in the science subject. An intervention to improve the delay of gratification in the science education context is teaching the subject of science using process skills to secondary school students. Experimental studies can hence be conducted where the control group students can be taught science using conventional methods, and the treatment group subjects can be taught science using process skills, and the impact of such a treatment on Science Delay of Gratification can be measured using this scale. Future studies must also direct their efforts to the development of mathematics, engineering, and technology variants of this scale.

5. Conclusion

The present study tried to develop a science education-specific delay of gratification scale in an economical manner, harnessing the advancements made in the field of artificial intelligence, by automatically generating psychological items based on a strong theoretical underpinning of the Cognitive-Affective Personality system. The scale was made parsimonious following a novel approach of applying the concepts of the Genetic algorithm and Nash equilibrium in Economics together, and validating it using the new approach of network psychometrics, along with the estimation of its measurement invariance capabilities using network comparison tests. Since all these aspects of the present research were primarily conducted using open sources like ChatGPT and RStudio, it is hoped that they will be continued and refined further in future studies pertaining to the psychological scale validation of multiple science education-related variables by practitioners and researchers of psychometrics.

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References

[1] Abd-El-Fattah, S.M. & Al-Nabhani, H.Z. (2012). From Self-Theories of Intelligence to Academic Delay of Gratification: The Mediating Role of Achievement Goals. Australian Journal of Educational and Developmental Psychology, 12, pp:93–107, http://files.eric.ed.gov/fulltext/EJ1002250.pdf.

[2] Arabzadeh, M., Kadivar, P. & Dlavar, A. (2012). The effects of teaching self-regulated learning strategy on students' academic delay of gratification. Interdisciplinary Journal of Contemporary Research in Business. 4(2), pp: 580-587.

[3] Bembenutty, H. & Karabenick, S. A. (2004). Inherent association between academic delay of gratification, future time perspective, and Self-Regulated learning. Educational Psychology Review, 16(1), pp:35–57. https://doi.org/10.1023/B:EDPR.0000012344.34008.5c

[4] Bembenutty, H. & Karabenick, S.A. (1998). Academic delay of gratification. Learning and Individual Differences, 10(4), pp.329–346. https://doi.org/10.1016/S1041-6080(99)80126-5.

[5] Bembenutty,H. & Karabenick, S.A. (1996). Academic Delay of Gratification Scale. A New Measurement for Delay of Gratification. Paper presented at the Annual Meeting of the Eastern Psychological Association (Philadelphia, PA, March 1996).

[6] Banwari, H. (2021). A Study of Various Factors that have contributed to the Alarming Surge in the Need for Instant Gratification in Generation-Z. International Journal of Indian Psychology, 9(3), pp:1880-1888.

[7] Battig, W.F. (1962). Parsimony in Psychology. Psychological Reports, 11(2), pp:555-572, https://doi.org/10.2466/pr0.1962.11.2.555.

[8] Bembenutty, H. & Karabenick, S.A. (2013). Self-Regulation, culture, and academic delay of gratification. Journal of Cognitive Education and Psychology, 12(3), pp: 323–337. https://doi.org/10.1891/1945-8959.12.3.323.

[9] Bringmann, L., Vissers, N., Wichers, M., Geschwind, N., Kuppens, P., Peeters, F., & Tuerlinckx, F. (2013). A Network Approach to Psychopathology: New Insights into Clinical Longitudinal Data. PLOS ONE, 8(4). https://doi.org/10.1371/journal.pone.0060188.

[10] Bhatt, S.A., Mir, A.A. & Islam,S.B. (2022). Scale Purification and Validation: A Methodological Approach to Sustainable Online Rating, The Journal for Decision Makers, 47(3), pp:217-234, https://doi.org/10.1177/02560909221123632.

[11] Bembenutty, H. (2007). Self-Regulation of learning and academic delay of gratification: gender and ethnic differences among college students. Journal of Advanced Academics, 18(4), pp:586–616. https://doi.org/10.4219/jaa-2007-553.

[12] Cobern W.W. & Aikenhead, G. (1997). Cultural Aspects of Learning Science. Scientific Literacy and Cultural Studies, Project. 13, Paper presented at the 1997 annual meeting of the National Association for Research in Science Teaching, Chicago, March 21-24, 1997.

[13] Chakraborty, R. & Chechi, V.K. (2024). Equivalence testing and Bayesian reliability estimation of volitional model: Instilling inferential nature in structural equation modeling, 3rd International Conference on Functional Materials, Manufacturing, and Performances. AIP Conference Proceedings. 2986, 030178-1–030178-8, https://doi.org/10.1063/5.0192649.

[14] Christensen, A.P., Golino, H., & Silvia, P.J. (2020). A Psychometric Network Perspective on the Validity and Validation of Personality Trait Questionnaires, European Journal of Personality, https://doi.org/10.1002/per.2265.

[15] Costantini, G., Epskamp, S., Borsboom, D., Perugini, M., Mõttus, R., Waldorp, L.J., & Cramer, A.O.J. (2014). State of the aRt personality research: A tutorial on network analysis of personality data in R, Journal of Research in Personality, https://doi.org/10.1016/j.jrp.2014.07.003.

[16] Dorrenbacher, L. & Perels, F. (2015). Volition completes the puzzle: Development and evaluation of an integrative trait model of self-regulated learning, Frontline Learning Research, 3(4), pp:14-36.

[17] Epskamp, S. (2016). Regularized Gaussian Psychological Networks: Brief Report on the Performance of Extended BIC Model Selection. arXiv:1606.05771.

[18] Epskamp, S. & Fried, E.I. (2018). A tutorial on regularized partial correlation networks. Psychological Methods, 23, pp:617–634. https://doi.org/10.1037/met0000167.

[19] Epskamp, S., Borsboom, D. & Fried, E.I. (2018). "Estimating Psychological Networks and their Accuracy: A Tutorial Paper." Behavior Research Methods, 50, pp. 195–212. https://doi.org/10.3758/s13428-017-0862-1.

[20] Epskamp, S., Cramer, A.O.J., Waldorp, L.J., Schmittmann, V.D., & Borsboom, D. (2012). "qgraph: Network Visualizations of Relationships in Psychometric Data." Journal of Statistical Software, 48(4), pp:1–18, 2012. https://doi.org/10.18637/jss.v048.i04.

[21] Götz, F.M. Maertens, R., Loomba, S. & van der Linden, S. (2023). Let the Algorithm Speak: How to Use Neural Networks for Automatic Item Generation in Psychological Scale Development. Psychological Methods. Advance online publication. https://doi.org/10.1037/met0000540.

[22] Haladyna,. T. (2004). Developing and validation multiple-choice test items. Routledge. https://doi.org/10.4324/9780203825945.

[23] Hommel, B.E., Wollang, F.J.M., Kotova, V., Zacher, H. & Schmukle, S.C. (2022). Transformer-based deep neural language modelling for construct-specific automatic item generation. Psychometrika, 87(2), pp: 749–772. https://doi.org/10.1007/s11336-021-09823-9.

[24] Homburg, C., Schwemmle, M., & Kuehnl, C. (2015). "New product design: Concept, measurement, and consequences", Journal of Marketing, 79(3), pp:41–56. https://doi.org/10.1509/jm.14.0199.

[25] Hudson, G. & Alexander, P.C. (2024). EGAnet: Exploratory Graph Analysis – A framework for estimating the number of dimensions in multivariate data using network psychometrics., R package version 2.0.7, https://r-ega.net. https://doi.org/10.32614/CRAN.package.EGAnet.

[26] Haslbeck, J.M.B. & Waldorp, L. J. (2020). "mgm: Estimating Time-Varying Mixed Graphical Models in High-Dimensional Data." Journal of Statistical Software, 93(8), pp: 1–46. 2020. https://doi.org/10.18637/jss.v093.i08.

[27] Hu, L.T. & Bentler, P,M. (1999). Cutoff Criteria for Fit Indexes in Covariance Structure Analysis: Conventional Criteria versus New Alternatives. Structural Equation Modeling, 6, pp:1-55. https://doi.org/10.1080/10705519909540118.

[28] Holland, P.W. & Thayer, D.T. (1988). Differential item performance and the Mantel-Haenszel procedure. In H. Wainer & H. I. Braun (Eds.), Test validity (pp. 129–145). Lawrence Erlbaum Associates, Inc.

[29] Jain, T., Mukhopadhyay, A., Prakash, N.& Rakesh, R. (2022). Science Education and Labor Market Outcomes in a Developing Economy, Economic Inquiry, 60(2). pp:741-763. https://doi.org/10.1111/ecin.13044.

[30] Kumar, R. & Singh, S. (2018).Aspects of science education in India: a synoptic review and possible directions for the future. Current Science, 114(9), pp:1825-1828. https://doi.org/10.18520/cs/v114/i09/1825-1828.

[31] Kahneman, D. & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. Econometrica, vol. 47, pp:263-291. https://doi.org/10.2307/1914185.

[32] Kivanju, C. (2014). Theoretical Perspectives of How Digital Natives Learn, International Journal of Higher Education, 3(1), pp: 94-109, https://doi.org/10.5430/ijhe.v3n1p94.

[33] Lee, P., Fyfee, S., Son, M., Jia, Z. & Yao, Z. (2023). A Paradigm Shift from "Human Writing" to "Machine Generation" in Personality Test Development: an Application of State-of-the-Art Natural Language Processing, Journal of Business and Psychology, 38, pp:163–190, https://doi.org/10.1007/s10869-022-09864-6.

[34] Lazarsfeld, P.& Henry, N. (1968). Latent structure analysis. New York: Houghton Mifflin.
[35] Lawshe, C.H. (1975). A Quantitative Approach to Content Validity. Personnel Psychology, 28, pp: 563-575. https://doi.org/10.1111/j.1744-6570.1975.tb01393.x.
[36] Lei, P..& Shiverdecker, L.K. (2019). Performance of Estimators for Confirmatory Factor Analysis of Ordinal Variables with Missing Data. Structural Equation Modeling a Multidisciplinary Journal, 27(4), pp: 584–601. https://doi.org/10.1080/10705511.2019.1680292.
[37] Mischel, W. (1981). "Metacognition and rules of delay of gratification." pp. 240-271 in Social cognitive development: Frontiers and possible futures, edited by J. H. Flavell & L. Ross, New York: Cambridge University Press.
[38] Mischel, W. (1973), "Toward a cognitive social learning re-conceptualization of personality." Psychological Review, 80(4), pp. 252-283. https://doi.org/10.1037/h0035002.
[39] Mischel, W. & Shoda,Y. (1995). A cognitive-affective system theory of personality: Reconceptualizing situations, dispositions, dynamics, and invariance in personality structure. Psychological Review, 102(2), pp.246-268, https://doi.org/10.1037/0033-295X.102.2.246.
[40] Manizia, L., Borah, T., Bhattacharjee, R., Saikia, J., Dutta, A., & Boruah, J. (2023). Instant Gratification and The Digital Natives: A Pilot Study, Educational Administration: Theory and Practice, 29(3), pp: 928-933, https://doi.org/10.53555/kuey.v29i3.7471.
[41] Midgley, C., Feldlaufer, H., & Eccles, J.S. (1989). Student/teacher relations a attitudes toward mathematics before and after the transition to junior high school. Child Development, 60, pp: 981– 992. https://doi.org/10.2307/1131038.
[42] Mahalanobis, P.C. (1936). On the generalized distance in statistics. Proc. Natn. Inst. Sci. India 2, pp: 49–55.
[43] Metcalfe, J., & Mischel, W. (1999). A Hot/Cool-system analysis of delay of gratification: Dynamics of Willpower. Psychological Review, 106(1), pp:3-19. https://doi.org/10.1037//0033-295X.106.1.3.
[44] Nash, J.F. (1950). Equilibrium points in n -person games. Proceedings of the National Academy of Sciences, 36(1), pp: 48–49. https://doi.org/10.1073/pnas.36.1.48.
[45] Pitt, M.A. & Myung, I.J. (2002). When a good fit can be bad. Trends Cogn Sci. 6(10):421-425. PMID: 12413575. https://doi.org/10.1016/S1364-6613(02)01964-2.
[46] Pijls,R. Groen, B.H., Galetzka,M. & Pruyn, A. T. (2017). Measuring the experience of hospitality: scale development and validation. International Journal of Hospitality Management, 67(1) , pp:125–133. https://doi.org/10.1016/j.ijhm.2017.07.008.
[47] Pe, M.L., Kircanski, K., Thompson, R.J., Bringmann, L., Tuerlinckx, F., Mestdagh, M., & Gotlib. I.H. (2015). Emotion-Network Density inMajor Depressive Disorder. Clinical Psychological Science, 3(2), pp: 292-300. https://doi.org/10.1177/2167702614540645.
[48] Peetsma, T.T.D. (1997). Decline in pupils' motivation during secondary education. Paper presented at the 7th European Conference for Research on Learning and Instruction, Athens.
[49] Peetsma, T.T.D., Hascher, T., Van der Veen, I. & Roede, E. (2005). Relations between adolescents' self-evaluations, time perspectives, motivation for school and their achievement in different countries and at different ages. European Journal of Psychology of Education, 20, pp: 209–225. https://doi.org/10.1007/BF03173553.
[50] [50] Peetsma, T.T.D., Schuitema, J. & Van Der Veen, I. (2012). A longitudinal study on time perspectives: Relations with academic delay of gratification and learning environment, Japanese Psychological Research, 54(3), pp:242-252, https://doi.org/10.1111/j.1468-5884.2012.00526.x.
[51] Podobnik, B., Crawford, G.C., Lichtenstein, B., Lipic, B.T., Wild, D., Zhang, X. & Stanley, H.E. (2020). The new wealth of nations: How STEM fields generate the prosperity and inequality of individuals, companies, and countries. Chaos Solitons & Fractals, 141, 110323. https://doi.org/10.1016/j.chaos.2020.110323.
[52] Prensky, M. (2001). Digital natives, digital immigrants part 1. On The Horizon, 9(5), pp:3 – 6, https://doi.org/10.1108/10748120110424816
[53] Rudner, L. (2010). Implementing the Graduate Management Admission Test computerized adaptive test. In W. van der Linden & C. Glas (Eds.), Elements of adaptive testing (pp. 151–165). Springer. https://doi.org/10.1007/978-0-387-85461-8_8.
[54] Ranjeeta, (2016). Attitude towards Science Education among Secondary School Students, International Journal of Research in Economics and Social Sciences (IJRESS), 6 (12), pp: 393-401.
[55] RStudio Team, (2019). RStudio: Integrated Development for R. RStudio, Inc., Boston, MA URL http://www.rstudio.com/.
[56] Revelle, W. (2017). psych: Procedures for Personality and Psychological Research, Northwestern University.
[57] Revelle, W. (2022). psychTools:Tools to Accompany the 'psych; Package for Psychological Research . Northwestern University, Evanston, Illinois. R package version 2.2.5, https://CRAN.R-project.org/package=psychTools.
[58] Romer,D., Duckworth, A.L., Sznitman,S. & Park, S. (2010). Can Adolescents Learn Self-control? Delay of Gratification in the Development of Control over Risk Taking, Prev Sci., 11(3), pp: 319-330, https://doi.org/10.1007/s11121-010-0171-8.
[59] Scrucca, L. (2013)."GA: A Package for Genetic Algorithms in R." Journal of Statistical Software, 53(4), pp:1–37. https://doi.org/10.18637/jss.v053.i04.
[60] Schroeders, U., Wilhelm, O. & Olaru,G. (2016). Meta-Heuristics in Short Scale Construction: Ant Colony Optimization and Genetic Algorithm. PLoS ONE, 11(11): e0167110. https://doi.org/10.1371/journal.pone.0167110.
[61] Schmittmann, V.D., Cramer, A.O.J., Waldrop, L.J., Epskamp, S., Kievit, R.A. & Borsboom, D. (2011). Deconstructing the construct: A network perspective on psychological phenomena, New Ideas in Psychology, https://doi.org/10.1016/j.newideapsych.2011.02.007.
[62] Sinclair, S. & Rockwell, G. (2016). Voyant Tools. Web. http://voyant-tools.org/.
[63] Soltani, A. & Askarizadeh, G. (2021). How students' conceptions of learning science are related to their motivational beliefs and self-regulation. Learning and Motivation, 73, 101707. https://doi.org/10.1016/j.lmot.2021.101707.
[64] Santos, L.S.Z., Souza, J.R., Alves De Cuna, J.V. & Avelino, B.C. (2018). Academic Delay of Gratification and Its Relation with Learning Self-Regulation Strategies, Journal of Education and Research in Accounting, 12(2), pp: 229-249, https://doi.org/10.17524/repec.v12i2.1693.
[65] Steinberg, L.A. (2008). Social Neuroscience Perspective on Adolescent Risk-Taking. Dev Rev. 28(1), pp:78-106, PMID: 18509515; PMCID: PMC2396566. https://doi.org/10.1016/j.dr.2007.08.002.
[66] Steidtmann, L., Kleickmann, T., & Steffensky, M. (2023). Declining interest in science in lower secondary school classes: Quasi-experimental and longitudinal evidence on the role of teaching and teaching quality. Journal of Research in Science Teaching, 60(1), 164–195, https://doi.org/10.1002/tea.21794.
[67] Testa, M.G. (2006). A influência das preferências por contato social e da autoregulação dos recursos de aprendizagem do estudante na efetividade dos cursos desenvolvidos na Internet. Tese de doutorado, Universidade Federal do rio Grande do Sul, Porto Alegre, RS, BrasilJenkins, L.(2011). Using citizen science beyond teaching science content: A strategy for making science relevant to students' lives. Cultural Studies of Science Education, 6, pp: 501–508. https://doi.org/10.1007/s11422-010-9304-4.
[68] Taranto, D. & Buchanan, M.T. (2020). Sustaining Lifelong Learning: A Self-Regulated Learning (SRL) Approach, Discourse and Communication for Sustainable Education. 11(1), 5-15. https://doi.org/10.2478/dcse-2020-0002.
[69] Vandekerckhove, J., Matzke, D., & Wagenmakers, E.J. (2015). Model comparison and the principle of parsimony. In J. R. Busemeyer, Z. Wang, J. T. Townsend, & A. Eidels (Eds.), The Oxford handbook of computational and mathematical psychology (pp. 300–319). Oxford University Press. https://doi.org/10.1093/oxfordhb/9780199957996.013.14.
[70] van Borkulo, C.D., van Bork, R., Boschloo, L., Kossakowski, J.J., Tio, P., Schoevers, R.A., Borsboom, D. & Waldorp, L. (2021). "Comparing network structures on three aspects: A permutation test." Psychological Methods. https://doi.org/10.1037/met0000476.
[71] Wigman, J. T. W., van Os, J., Borsboom, D., Wardenaar, K. J., Epskamp, S., Klippel, A., & Wichers, M. (2015). Exploring the underlying structure of mental disorders: cross-diagnostic differences and similarities from a network perspective using both a top-down and a bottom-up approach. Psychological Medicine, 45(11), pp: 2375-2387. https://doi.org/10.1017/S0033291715000331.
[72] Wohner, F. & Franzen, A. (2024). The Impact of Answer Scale Orientation on the Measurement of Life Satisfaction, Journal of Happiness Studies, 25(78), https://doi.org/10.1007/s10902-024-00798-9.

[73] Wieland, A., Durach, C.F., Kembro, J. & Treiblmaier, H. (2017). Statistical and judgmental criteria for scale purification. Supply Chain Management: An International Journal, 22(4), pp: 321–328, https://doi.org/10.1108/SCM-07-2016-0230.
[74] Xie, Y., Fang, M., & Shauman, K. (2015). STEM Education. Annu Rev Sociol. 1;41:331-357. Epub 2015 May 4. PMID: 26778893; PMCID: PMC4712712. https://doi.org/10.1146/annurev-soc-071312-145659.
[75] Zickar, M.J. (2020). Measurement development and evaluation. Annual Review of Organizational Psychology and Organizational Behavior, 7, pp: 213–232, 2020. https://doi.org/10.1146/annurev-orgpsych-012119-044957.