MEASUREMENT INVARIANCE TESTING OF THE REVISED INTEGRATIVE TRAIT MODEL OF SELF REGULATED LEARNING AMONG ENGINEERING UNDERGRADUATES

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EDUCATION

By

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Transforming Education Transforming India

LOVELY PROFESSIONAL UNIVERSITY

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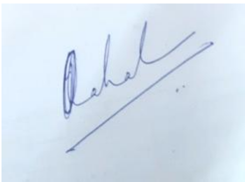
DECLARATION

I do hereby declare that the thesis entitled ***"Measurement Invariance Testing of the Revised Integrative Trait Model of Self Regulated Learning among Engineering Undergraduates"*** has been prepared and submitted by me under the guidance of Dr. Vijay Kumar Chechi, Professor and Head, School of Education, Lovely Professional University, Phagwara, Punjab, as per the full requirement for the award of the degree of Doctor of Philosophy (Ph.D) in Education is entirely my original work and all ideas and references have been duly acknowledged. It does not contain any work that has been submitted for the award of any other degree or diploma of any university.



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CERTIFICATE

This is to certify that Mr. Rajib Chakraborty has completed Doctor of Philosophy (Ph.D.) in Education Thesis titled ***"Measurement Invariance Testing of the Revised Integrative Trait Model of Self Regulated Learning among Engineering Undergraduates"*** under my guidance and supervision. To the best of my knowledge, the present work is the result of his original investigation and study. No part of the thesis has ever been submitted for any other degree or diploma to any other university. The thesis is fit for the award of Doctor of Philosophy (Ph.D.) degree.

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ABSTRACT

In the 21st century, no university in the world can prepare a work force that is tailor made for any industry vertical. The professional relevance of an individual is dependent on the extent of flexibility shown by him or her in acquisition of new knowledge, skill and attitude through lifelong learning. This is possible only through display of self regulation or autonomy in learning throughout the life. Owing to its comprehensiveness, the phenomenon of self regulated learning encompasses within it, a large number of variables spread across five known components. These five components are spread across cognition, meta-cognition, motivation, emotion and behavior. The state of the art empirical trait based model of self regulated learning encompasses the first three components. Lack of reliable tool to measure the academic emotional analogue of self regulated learning was a block on the way of further research. But, the development of the academic emotional regulation questionnaire by Buric et al. (2016) addressed this issue. Also, the measurement of the individual difference of this vital construct of self regulated learning is possible only if a comprehensive, empirical and parsimonius trait based model is available. The present research tried to present an integrative model in the Indian context on the basis of Buric et al. (2016) and Cazan (2012) work guided by the latest trait based self regulated learning model of Dorrenbacher and Perels (2015). Quantitative descriptive survey design was adopted here. A host of tools pertaining to 14 identified self regulated learning variables measuring the five components were chosen, adopted and purified as per the requirement in the Indian context. The population chosen for this study was engineering undergraduates of the Punjab state of India. This is due to the primer role of engineering discipline in driving the Indian economy and for the engineering graduates being the most sought by the employers in India. The issues of drop-outs from this program and production of poor quality engineers were also targeted while selecting the mentioned population as established by literature review. Two of the most sought after streams of engineering discipline, as per AISHE 2019 report, the Computer Science Engineering and Mechanical Engineering were selected for choosing the participants or the sample of the study. The engineering program is offered in the state of Punjab by both AICTE recognized engineering colleges and

UGC recognized universities which have the approval of AICTE in teaching the courses of this program. The number of institutions in the three regions of the state, Majha, Doaba and Malwa were estimated and the number of institutions to visit was found based on stratified random sampling technique. Seven foreign tools were validated, adopted and purified as part of pilot study. The items of these tools were later subjected to differential item functioning technique to reveal their invariance with respect to gender. The classical test theory and item response theory based estimates of these items were compared to look for congruence in results. The final tool to measure the trait based SRL comprised of 62 items with 5 fillers in them. Sample size determination for effect size 0.3, power 0.9, level of significance 0.05, number of latent variables 14 and number of observed variables 62, revealed the estimate to be 252. The final data was subjected to mahalanobis test for the detection of outliers, followed by the determination of the polychoric confidence interval alpha and omega reliability estimation meant for Likert scale based ordinal data. Then, the intactness of the proposed comprehensive model of trait based self regulated learning was estimated using confirmatory factor analysis followed by the measurement invariance testing of the over-all model with respect to gender, batch and stream of engineering for a final sample size of 533. The academic emotional regulation questionnaire with its eight dimensions and 36 items, barring one item, displayed excellent validity and reliability estimates when adapted in the Indian context from Croatia. The volitional component of motivation, comprised of academic delay of gratification, future time perspective and academic procrastination variables as put together and validated in the German context by Dorrenbacher (2015) was found to be valid in the Indian context too. The model involving volition as a sub component under motivation component of self regulated learning performed better psychometrically as found by Dorrenbacher (2015) using three components of self regulated learning. Consequently, the revised integrative trait model of self regulated learning was found to be display acceptable psychometrics with the application of Structural equation modeling (SEM) technique on it. Finally, the revised integrative trait model of self regulated learning was found to be measurement invariant with respect to gender, batch and stream in the context of IInd and IIIrd year Computer Science Engineering and Mechanical Engineering undergraduates of Punjab state in

India. The limitations of this study, based on Structural equation modeling, like the unresolved issues of multicollinearity(Tarka, 2018) and reliability paradox (Hancock and Mueller, 2011), were discussed, along with other data collection related constraints. The implications of the study findings, in the context of India being a signatory nation of Washington Accord, hold due cognizance. Also, the availability of a measurement invariant tool to comprehensively measureself regulated learning can prove handy for the academician in initiating the profiling of engineering students to address the menace of sophomore slump. It can further lead to designing of intervention programs to promote this vital construct, intimately related to academic achievement and life long learning, in engineering institutions ultimately leading to the advancement of engineering education in our country through its scientific streamlining. This research also introduced and shared the codes of some of the state of the art statistical techniques of scale purification like Ant Colony Optimization (ACO), Network Psychometrics based Exploratory Graph Analysis (EGA) and Ordinal Confirmatory Factor Analysis, Parametric and Non-parametric Item Response Theory (PIRT and NIRT) based Item selection, Latent Profile Analysis (LPA), Differential Item Functioning (DIF) based measurement invariance of items, and the measurement invariance testing of the SEM models, to improve the standards to tool validation in general. The blanket reporting of Cronbach's alpha by assuming the data obtained from Likert scale based questionnaires to be interval in nature and the underestimation of true reliability of the scales are adequately addressed by discussing the conditions of tau-equivalence and sharing the R codes to obtain the Polychoric omega reliability for ordinal likert scale based questionnaire data. With all these state of the art techniques conducted in R/RStudio freeware with their codes shared, it is hoped that these minuscule advancements would prove helpful to further the awareness on availability of robust statistical techniques through freewaresand their successful implementation in Indian psychometrics researchin general.

Keywords:*Measurement Invariance,Trait-based Self Regulated Learning, Engineering Undergraduates, Engineering Education, PolychoricAlpha Reliability, PolychoricOmega Reliability,Ant Colony Optimization (ACO), Network Psychometrics, Latent Profile Analysis (LPA), Exploratory Graph Analysis (EGA),*

Ordinal Confirmatory Factor Analysis, Parametric Item Response Theory (PIRT) and Non-parametric Item Response Theory (NIRT), Differential Item Functioning (DIF), Reliability paradox, Sophomore Slump, Structural Equation Modeling, Indian Psychometrics Research.

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I dedicate this terminal degree to my parents whose only dream was to see their son get educated, towards which they slogged relentlessly during their lifetime. I miss their presence this day to bits.

Dated:………………..

Rajib Chakraborty

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LIST OF ABBREVIATIONS

S.NO.	ABBREVIATI	FULL FORM
1	AA	Academic Achievement
2	AP	Academic Procrastination
3	AIM	Academic Intrinsic Motivation
4	AERQ	Academic Emotion Regulation Questionnaire
5	AIC	Akaike Information Criterion
6	AGFI	Adjusted Goodness of Fit Index
7	AICTE	All India Council for Technical Education
8	AMOS	Analysis of Moment of Structures
9	ADGS	Academic Delay of Gratification Scale
10	ADOGS	Academic Delay of Gratification Scale
11	ACO	Ant Colony Optimization
12	BIC	Bayesian Information Criterion
13	CFI	Confirmatory Factor Analysis
14	CMIN/DF	Chi-Square / Degree of Freedom
15	CI	Confidence Interval
16	CSE	Computer Science and Engineering
17	CGPA	Cumulative Grade Point Average
18	CR	Composite Reliability
19	CTT	Classical Test Theory
20	DIF	Differential Item Functioning
21	DMM	Double Monotonicity Model
22	EFA	Exploratory Factor Analysis
23	EGA	Exploratory Graph Analysis
24	FL	Factor Loading
25	FP	Fitting Parameter
26	FTP	Future Time Perspective
27	GFI	Goodness of Fit Index

28	GPA	Grade Point Average
29	GRM	Graded Response Model
30	GLB	Greatest Lower Bound
31	GGM	Gaussian Graphical Model
32	GO	Goal Orientation
33	HDS	Homework Distraction Scale
34	IRT	Item Response Theory
35	IBEF	India Brand Equity Foundation
36	IEEE	Institute of Electronic and Electrical Engineers
37	ICC	Item Characteristic Curve
38	IIC	Item Information Curve
39	IFI	Incremental Fit Index
40	KSAM	KernalSmooting Approach Model
41	K-Index	Kumagai Index
42	KMO	Kaiser-Meyer-Olkin
43	LASSO	Least Absolute Shrinkage and Selection
44	LPA	Latent Profile Analysis
45	LISREL	Linear Structural Relations
46	LRT	Likelihood Ratio Test
47	MHM	Monotone Homogeneity Model
48	MAP	Minimum Average Partial Procedure
49	ME	Mechanical Engineering
50	MSLQ	Motivated Strategies for Learning Questionnaire
51	MSLQ – R	Motivated Strategies for Learning Questionnaire – Revised
52	MAI	Metacognitive Awareness Inventory
53	MI	Measurement Invariance
54	MASRL	Metacognitive and Affective Model of Self Regulated Learning
55	MG CFA	Multi Group Confirmatory Factor Analysis
56	NBA	National Board of Accredation

57	NIRT	Non-parametric Item Response Theory
58	NCI	Non-centrality Index
59	OMQ	Online Motivation Questionnaire
60	PIRT	Parametric Item Response Theory
61	PIRT	Parametric Item Response Theory
62	PCA	Principal Component Analysis
63	PMRF	Pair-wise Markov Random Field
64	QESE	Questionnaire of English Self Efficacy
65	QESRLS	Questionnaire of English Self Regulated Learning Strategies
66	RMSEA	Root Mean Square Error of Approximation
67	RMR	Root Mean Square Residual
68	SE	Self Efficacy
69	SRL	Self Regulted Learning
70	SRMR	Standardized Root Mean Square Residual
71	SAL	Student Approaches to Learning
72	SEM	Structural Equation Modelling
73	STEM	Science Technology Engineering Mathematics
74	SWE	Society of Women Engineers
75	SAQ	Self Assessment Questionnaire
76	SESRL	Self Efficacy for Self Regulated Learning
77	TLI	Tucker Lewis Index
78	TLI	Tucker Lewis Index
79	TVE	Total Variance Explained
80	TIC	Test Information Curve
81	TSDY	Time and Study Environment
82	UGC	University Grants Commission

83	WLSMV	Weighted Least Square Mean Variance
84	ZTPI	Zimbardo Time Perspective Inventory

LIST OF SYMBOLS

S.No.	Symbol	Full Form
1	α	Cronbach's Alpha
2	λ	Guttman's Lambda
3	ω	McDonald's Omega
4	θ	Ability Level
5	P(θ)	Probability of Response
6	df	Degree of Freedom
7	COG	Cognitive Component of Self Regulated Learning
8	META	Meta -cognitive Component of Self Regulated Learning
9	MOT	Motivational Component of Self Regulated Learning
10	MB	Motivational Belief
11	VOL	Volitional Component of Self Regulated Learning
12	EMO	Emotional Component of Self Regulated Learning
13	BEH	Behavioral Component of Self Regulated Learning

CHAPTER 1

INTRODUCTION

The Indian annual budget of 1991, presented in the Parliament by the then Finance minister Dr. Manmohan Singh was a watershed moment in the annals of Indian economy. It opened the Indian markets for investments from the foreign countries, ease the trade regime, increased the choices for the consumers and brought down poverty significantly. Trodding on the same path, the successive finance ministers, in the last three decades, strengthened the policy and made India one of the leading economies of the world.

In the present scenario, capitalizing on the demographic fact that 65 percent of the Indian population is less below the age of 35 years and the global labor market being increasing integrative in nature, the emerging economies like India, are harnessing the opportunity of providing a large pool of labor to the global work force. However, in order to maintain the steam, the Indian education sector, at both, the school and university levels, must ensure meeting the global 21st century competences framework.

One of the major competencies that a 21st century learner must acquire is becoming autonomous with respect to his or her learning (Wolters, 2010). It leads to achievement of one of the major roles of education, namely, life long learning (Zimmerman, 2002). The significance of life-long self dependent learning is emphasized in the 21st Century Competencies (21 CC) framework document as well (Ananiadou and Claro, 2009; Jerald, 2009), which proclaims delivering of knowledge, skills and attitudes to the students so that they can prepare for life in the decades to come, instead of merely being noticed at the alma mater or the workplace.

The phenomenon of exercising autonomy in learning from the student's perspective, is studied under the umbrella term Self regulated learning in Educational Psychology.It is a comprehensive term and encompasses a large number of variables inside it with multiple facets to deal (Panadero, 2017). Owing to its intimate relationship with academic achievement in multiple tiers of different education system, research on this construct is pertinent than ever before (Dignath, Buttner and Langfeldt, 2008; Kitsantas, Winsler and Huie, 2008).

1.1 Background of Self Regulated Learning (SRL)

One of the most widely used cognitive theories explaining self regulated learning in educational settings, is the Social cognitive theory of Bandura (1986). It states that the functionings in the humans happen due to reciprocal interactions among three factors, namely, personal (like cognitions and emotions), behavioral and environmental.

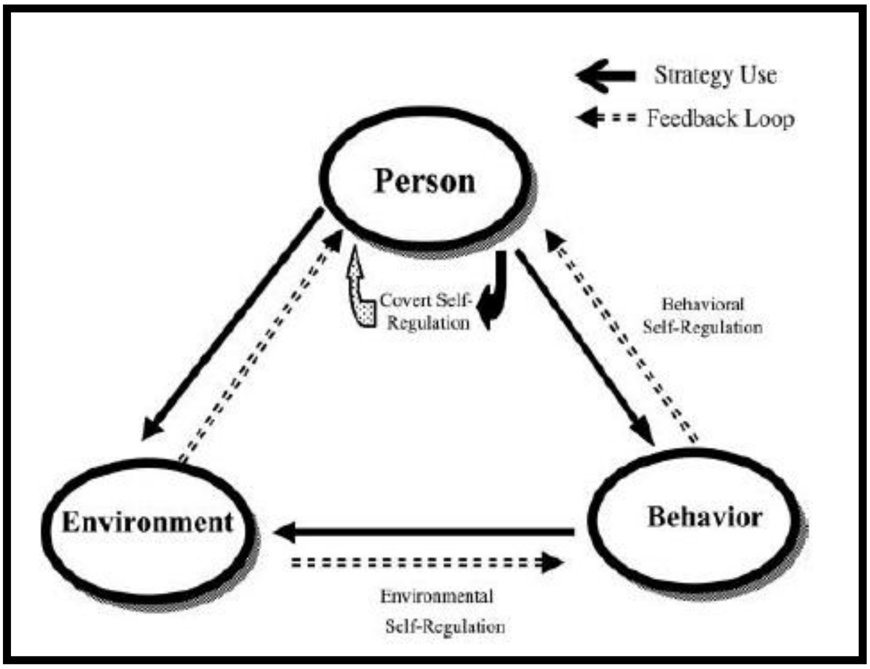


Figure 1.1 **Triadic model of self-regulation (Zimmerman, 1989)**

Zimmerman (1986) conceptualized self regulated learning (SRL) from social cognitive theory of Bandura as "the extent that students are cognitively, motivationally, and behaviorally "active participants" in an academic task (p.308)" and it consists of a cyclic loop with four phases: forethought, monitoring, control, and reaction and reflection.

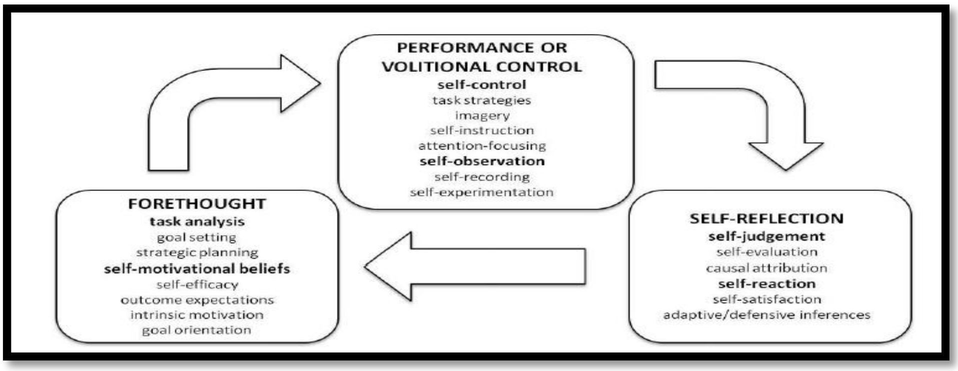


Figure 1.2 **Social-cognitive process model of self-regulation (Zimmerman, 2000).**

Zimmerman (1990, 2008, 2013) operationalizedSRL as “dynamic and cyclical processes that consist of three independent phases: forethought, performance, and self-reflection”. The construct of self-regulation (Zimmerman, 2000) is not tied to a specific domain or research area, and it can be transferred easily to different domains. Therefore, it can be applied to learning processes and is then called *self-regulated learning (SRL)*. When a learner is experiencing the phases of SRL, he or she employs a variety of learning strategies in motivational, cognitive, behavioral, and contextual domains for goal attainment. Zimmerman and Schunk (2001) later referred to self regulated learning as “the way students manage their feelings, thoughts and actions to perform well in studies”. According to Pintrich (2000), self-regulated learning refers to an “active, constructive process whereby learners set goals for their learning and then attempt to monitor, regulate, and control their cognition, motivation, and behavior, guided and constrained by their goals and the contextual features of the environment”.

As a concept, it is seen as a relatively stable attribute in any situation, that is, as a trait, that influences an individual’s processes of learning in general (Boekaerts, 1999), or, as a state of mind, that changes dynamically according to the demands of the situation (Schmitz and Wiese, 2006). However, Matthews et.al (2000) treated it as both a trait and a state. According to Hong (1995), states get affected by their respective traits and individual differences of a construct can be studied by treating it as a trait (Hong and O’Neil, 2001).

Though self regulated learning encompasses components belonging to cognitive, metacognitive, behavioural, motivational and emotional perspectives of learning, most of the researchers agree that SRL can be mainly studied under its cognitive, metacognitive and motivational components and their reciprocal relationships (Boekaerts, 1999). The interrelationships of the components of self regulated learning and the role of the variables within these components are holistically studied under the models of self regulated learning.

1.2 Introduction to the History of Self Regulated Learning Theoretical Models:

Initially, there were two perspectives based on which models on self regulated learning emerged. These perspectives were namely Student Approaches to Learning (SAL) and information processing approach (IP) (Biggs, 1993; Dyne et al., 1994; Entwistle and Waterson, 1988). SAL models were based on gathering data from the students on their sources of motivation, studying and learning within the contexts of colleges and university with the help of interviews (Biggs, 1993; Dyne et al., 1994; Entwistle and Waterson, 1988; Marton and Saljo, 1976), and quantitative studies using surveys and questionnaires and hence they were called bottom-up approach. On the contrary, the IP approach was top-down in nature, as it started from psychological theories and constructs emerging from cognitive and educational psychology and ended with their substantiation through empirical observations on college and university students (Biggs, 1993; Dyne et al., 1994; Entwistle and Waterson, 1988).

The perspective of information processing was replaced by self regulated learning perspective (Pintrich, 200b; Winne and Hadwin, 1998; Zimmerman, 2000) as the IP perspective was found to be limited and incapable of representing the advances in theory and research. SRL perspective around the year 2000 was broad enough to accommodate cognitive, motivational, affective and social contextual factors into the research on college and university students. But, in the present time, inclusion of the new volitional component and its associated variables into a comprehensive model of self regulated learning is imperative (Dorrenbacher and Perels, 2015) as an advancement of SRL perspective and along with its emotional component (Buric et al., 2016; Ben-Eliyahu and Linnenbrink-Garcia, 2013).

Most SRL models are based on four basic assumptions (Boekarts, Pintrich and Zeidner,2000). They are ***active constructive assumption*** (the learner is an active participant and the creator of the meaning of the content to be learnt), ***potential for control assumption*** (the learner to some extent can exercise control over their cognition, motivation, behavior and external environments), ***goal, criterion, or standard assumption*** (the learner has a set goal or a criterion against which he or she measures the process of learning and accordingly regulates further learning strategy) and ***SRL activities being mediators between personal and contextual characteristics, and academic achievement*** of the students.

While there is agreement on first and fourth assumptions, SAL and SRL perspectives disagree on second and third assumptions. Moreover, SAL has a bottom-up approach using the phenomenological studies based on students' own reports about learning processes, and SRL has a top-down approach which leads to conception of constructs based on analysis and application of models of learning rooted in educational psychology theories, substantiated by quantitative data.

The biggest difference is that while SAL tries to analyze general approaches to learning and prepare a global construct system, SRL focuses on specific phases of learning through its models hence allowing the scope to regulate its components like cognition and motivation and develop new psychological constructs and categories in student learning. (Pintrich, 2004). Taking the ability of the self report instruments like questionnaires and survey as assessment instruments, to capture micro-level processes into consideration (Winne and Perry, 2000; Winne et al.,2001) as an advantage, the present study is based on trait models of SRL top-down perspective.

1.3 Introduction to the History of Self Regulated Learning Empirical Models:

Zimmerman (1986) was one of the first authors of SRL concept. The first model of SRL which provided its separate status from metacognition, was published by him in 1989, in which Zimmerman (1989) explained self regulation not as a process to occur at individual level, but requiring interactions with the environment, in addition to the presence of personal and behavioral influences, as part of his social-cognitive view of SRL.

Presently, there are several models of SRL (Sitzmann and Ely, 2011). But, those models which underwent considerable development and were supported by empirical studies are five in number. They are the models of Borkowski (1996), Winne (Winne and Hadwin, 1998), Boekaerts (Boekarts and Niemivirta, 2000), Pintrich (2000) and Zimmerman (2000a). These five models can be broadly classified under two definitions of SRL namely the goal-oriented and metacognitively weighted definitions of SRL. For Boekearts, Pintrinch and Zimmerman, SRL is a goal-oriented process involving the regulation of one's learning with the help of cognitive, motivational, emotional and social factors. Borkowski and Winne treated SRL as a process governed by metacognition and use of strategies and tasks of cognition to perform tasks.

The goal-oriented definition of SRL prevails ultimately owing to the fact that even Borkowski and Winne's theory work on the assumption that self regulated learners are motivated intrinsically and goal oriented by nature. So, models from both the definitions of SRL are not much different from each other and it is the relative significance, that a model gives to a particular component that differentiates one from the other (Puustinen and Pulkkinen, 2001).

In recent times, the Metacognitive and Affective Model of Self-Regulated Learning (MASRL) by Efklides (2011) has been cited several times and garnered much attention. This model presents two levels, namely, the Person's level or the macro-level composed of cognition, metacognition, motivation, self-concept, affect and volition, and the Task X Person level, also known as micro-level where interaction with the previous level takes place leading to the functions like metacognition, affect and motivation. However, the theory does not discuss above the behavioral component of SRL.

All the models of SRL, irrespective of the terminology used to describe themselves, pass through three phases namely, the preparatory phase, the performance phase and the appraisal phase.

Table 1.1 Elements of a model as per the Phases of SRL Process			
Author's Model	**Phases of SRL**		
	Preparatory	**Performance**	**Appraisal**
Boekaerts	Identification, interpretation, primary and secondary appraisal, goal setting	Goal striving	Performance feedback
Borkowski	Task analysis, strategy selection	Use of strategy, its revision and monitoring	Performance feedback
Efklides	Task Representation	Cognitive processing, performance	-
Hadwin et al., 2011	Planning/ Negotiating and awareness of the task	Monitoring, control / strategic task engagement	Regulating / adaptation
Pintrich	Forethought,planning, activation	Monitoring, control	Reaction and reflection
Winne and Hadwin	Task definition, goal setting and planning	Applying tactics and strategies	Adapting metacognition
Zimmerman	Forethought (task analysis, self motivation)	Performance (self control self observation)	Self reflection (Self judgement and self reaction)

Table 1.2 Comparison of Models related to Cognition, Motivation and Emotion			
Relevance Levels Read as a Continuum	**Cognition**	**Motivation**	**Emotion**
First (Most stressed)	Winne Efklides SSRL	Zimmerman, Boekaerts, Pintrinch	Boekaerts
Second	Pintrinch, Zimmerman	SSRL Efklides Winne	Zimmernan / Pintrinch SSRL
Third (least stressed)	Boekaerts	-	Efklides Winne

The frontline study presenting the latest comprehensive model of SRL, integrating the much neglected (Garcia et al., 1998) and much demanded (Duckworth et al., 2014; Wolters and Benzon, 2013; Zimmerman, 2008) volition component along with cognition, metacognition and motivation components, was presented by Dorrenbacher and Perels (2015). The study suggested adding of intelligence, attitude or personality related variables in the existing model to enhance its validity, through the prediction of academic achievement using GPA. It also suggested future research to be conducted to prove the measurement invariance of the comprehensive model with respect to gender.

A comparison of the state of the art existing models of SRL (excluding Dorrenbacher and Perels, 2015) in educational psychology was conducted by Panadero (2017), who drew an important conclusion that depending on the educational level of the students, the interventions of SRL vary in effects. While at primary level, students get benefited with interventions involving motivational and emotional aspects (Dignath et al., 2008), at secondary education level, interventions involving metacognitive aspects can be fruitful (Dignath and Buttner, 2008). Based on this study, Panadero (2017) hypothesized that metacognitive models of SRL would be having greater impact at secondary educational level and at higher education level, the motivational component is more important (Sitzmann and Ely, 2011). These hypotheses require testing, as the metacognitive and motivational components are parts of the comprehensive SRL model.

While the literature on SRL is rich with description of the cognitive, metacognitive and motivational components along with their respective variables, the description of research on volitional component and its respective variables is available discreetly and not under the umbrella term of SRL research. The variables academic delay of gratification, procrastination and future time perspective represent volitional strategies in learning conditions (Steel, 2007). Since the above study provided volition its rightful place within the framework of SRL, a discussion on the background of it and its components, within the empirical ambit, becomes imperative.

1.3.1 Volition:

According to Corno and Kanfer (1993), volition is a relatively stable individual difference in the personality that influences goal choices and working towards action control processes and is based on the action-control theory of Kuhl (1985). In this theory, Kuhl discusses that individuals experience implement a particular action in a specific situation which is the strongest or dominent among a host of competing action tendencies (Atkinson and Birch, 1970).The dominant action is the one which possesses the maximum utility value on its completion with regard to the consequences among a host of alternatives (Kuhl, 1982a). Inspite of the pressure exerted by these competing tendencies, individuals continue to work towards the achievement of a goal. This is possible only when there is a mechanism in place which stops the other competent tendencies from becoming dominant and reducing the strength of the current intention, before the set goal is achieved by an individual. Hence, the birth of the concept of volition. According to Kuhl, such a mechanism mediates self regulatory functions, in which a motivational tendency is looked upon separately to intention. This is owing to the consideration that an intention has higher quality of commitment over a motivational tendency. Activation of the self regulatory strategies, marked by an intention, takes place when the difficulty of doing an action amidst strong competing tendencies surpasses a critical value and the perceived ability of the individual to complete a task amidst these distractions surpasses another critical value. There are six self regulated strategies which the current intention from becoming dormant and stop any of the competing tendencies to become dominant until the completion of task. These strategies are *active attentional selectivity* (which processes information pertaining to current intent and does not process information related to competing tendencies), *encoding control* (which the volition protective function under which encoding of those stimulus takes place which are related to current intent), *emotion control* (which protects volition from getting affected to emotional states), *motivation control* (which is feedback provided by self regulatory processes to their motivational sources), *environmental control* (it is born out of the manipulation of emotions and motivations), *parsimony of information processing* (it helps in deciding when to stop gathering and processing information, and start acting, thus optimizing the length of decision making process).

McCann and Garcia (1999) stressed on the empirical inclusion of volition strategies into self regulated learning framework. A host of variables are reported to be existing within the ambit of this relatively new component of self regulated learning, out of which, the highly correlated ones according to Bembenutty and Karabenick (2004) are mentioned below:

1.3.1.1 Academic Delay of Gratification:

An important variable associated with self regulated learning is delay of gratification. Mischel (1984) linked delay of gratification with self regulated learning, to be later supported by the works of Zimmerman (1986) who found that self regulated learners posses the ability to keep their focus in tact by protecting task-specific intentions from non-task alternatives by keeping away from the distractive options. Delay of gratification represents "people's attempts to delay immediate smaller gratification for the sake of more desirable but distant goals"(Mischel, 1981, p. 244).

`Successful self-regulators engage in academic delay of gratification by deferring attractive activities (for example, going to a party with friends) in order to achieve long-term goals for example, studying for an examination). In contrast, less successful self-regulators engage in immediate gratification that could preclude academic success (Bembenutty, 2007, 2009).

According to Metcalfe and Mischel (1999), individual differences in delay of gratification can be explained through the theory of Hot and Cool systems. As per this theory, there are two centers of decision making in the brain. Individuals with the more active proposed hot system, are emotional, impulsive and reflexive in nature, and experience fear and passion as part of emotional conditioning. The individuals with the active cool system are more cognitive, contemplative, emotionally neutral, slow, strategic, flexible and represent self regulation through self control. The ability to strike a balance between these two systems is determined by the extent of self regulation present in the individual, current stress and developmental levels. The interactions between the hot and cool systems explain the research findings on the variable delay of gratification.

Delay of gratification is a multi-dimensional construct (Bembenutty, 1999; Durden, 1997; Ward et al. 1989). In order to understand it better, all the dimensions are to be broken down and analyzed. One such dimensions of concern is academic delay of gratification. Researchers like Bembenutty and Karabenick worked towards the presentation of a construct that was delay of gratification, but in academic settings. Having coined the term academic delay of gratification, Bembenutty and Karabenick (1996) operationally defined it as *"*the willingness to postpone immediately available opportunities to satisfy impulses in favor of academic goals that are temporally remote but ostensibly more valuable". They developed the 10-item Academic Delay of Gratification Scale (ADOGS) which is a gold standard to assess individual differences in this construct and related it with self-regulated learning (Bembenutty and Karabenick,2002). Academic delay of gratification is defined as "postponing proximate, impulse satisfying actions to sustain previously intended actions oriented towards a distant but apparently more valuable academic goal" (Bembenutty, 2008), and in this way has volitional nature (Bembenutty & Karabenick, 2004).

Goleman (1995) showed that the individual differences in delay of gratification can be significantly related to emotional intelligence. Emotional self regulation or impulse control has a vital role to play in delaying gratification. The ability to understand emotions and the casual relationships between different states of affection is a fundamental condition to properly predict the real value of a reward in future and wait for it. The ability to include emotion in thinking helps in rational decision making by showing the individual what immediate and delayed rewards have as their respective affective consequences. This clarity helps the individual to choose the latter option. Also, effective management of emotions helps in controlling the impulses or tendencies to have instant pleasure or seek immediate rewards.

Chakraborty (2016) presented a narrative review of the foreign origin research work conducted on academic delay of gratification construct from its inception year to 2016. It is owing to the indications of this variable being culturally sensitive. One of the earlier studies linking culture and delay of gratification was conducted by Michel (1961) where he found the children from one sub-culture, Trinidad island, to possess less delay of gratification, than children from another sub-culture, Granada island, in West Indies. Later, Bembenutty and host of other researchers all over the world adopted and validated the scale to measure academic delay of gratification in multiple countries of varied cultures (Chakraborty, 2016).

In the Indian context, Chakraborty et al. (2015, 2016, 2017) found positive and significant relationship between emotional intelligence and academic delay of gratification in secondary school students, student teachers and professional courses students, along with establishing the association of academic delay of gratification with academic volition and dispositional optimism. Chakraborty (2017a) validated the academic delay of gratification scale in the Indian context, estimated its greatest lower bound limit (Chakraborty, 2017b), and verified its metric invariance with respect to gender (Chakraborty, 2017c). Sindhu (2017), who cited the researcher's previous work (Chakraborty, 2017a), found a significant relationship between academic delay of gratification and parenting style in the context of self regulated learning in Physics. Female gender is more sensitive to the construct academic delay of gratification than male students and so are government, aided, unaided, rural and urban school students.

Chakraborty and Chechi (2018) found that relationship between the factor structure of the construct academic delay of gratification and sample size, and reported an improvement in the measures of the factor structure up to the item to sample size of 1:30. The measures showed no appreciable improvement for the higher item to sample size ratio. The researcher till now established the relationship of academic delay of gratification with other self-regulation variables in terms of association and predictions, using correlation and regression techniques, in the Indian context. The role of academic delay of gratification amidst a host of self regulation learning variables and as a part of a structural model or latent variable model, remained unexplored and hence the need of this study.

1.3.1.2 Future Time Perspective:

Wallace (1956) coined and proposed the earliest definition of future time perspective based on the works to Lewin (1951) and Frank (1939). It contained two concepts namely, extension and coherence. Extension is "the length of future time span that is conceptualized”. Coherence is “the degree of organization of events in the future time span”.

Carstensen (1993) and Carstensen et al. (1999) presented the Socio-emotional selectivity theory of future time perspective which forecasted that an individual selects future goals based on the time available to live. If the time is more, the individual would selects goals which would enrich his future, either through acquisition of knowledge or through meeting people who would be helpful to him in near future. When the time left is less for an individual, he or she prefers to spend such a time in emotionally sensible goals as they can be achieved and experienced in shorter period of time. The theory also says that non-relationship between goals and future time perspective can be detrimental for the individuals leading to impatience, disappointment and irritation with others when they fail to meet the expectations. When goals are congruent with future time perspective, the individuals plan and engage in future activities even if they involve risks.

Nuttin (1964) related future time perspective to learning and cognitive theories of human motivation and defined future time perspective as “The psychological future is essentially related to motivation. On the behavioral level the object needed is something to come, to reach, or to achieve, and this constitutes the behavioral future. Thus, the future is the time quality of the goal object; the future is our primary motivational space, (p. 63).” He also explained the reason for the past to get maximum attention in the theories of learning involving conditioning, than the future component of time in the form of anticipation, and separated the two aspects.

Raynor (1970) talked about the relationship between achievement motivation and future time perspective based on theory of achievement motivation (Atkinson and Feather, 1966) and its elaborated version. Students displayed enhanced achievement motivation when certain activity ensured their immediate as well as future success in career, than mere immediate success.

According to de Volder and Lens (1982), students who scored higher grade point average attached more value to the goals in distinct future and believed in sustained placement of effort as instrumental in the realization of the goals. They conceptualized future time perspective as consisting of dynamic and cognitive aspects respectively. While the former involves a disposition to assign high value to tasks of distinct future, the latter involves a disposition to figure out the consequences in the long run of the actual behavior.

Carstensen and Lang (1996) developed the first tool to measure future time perspective college students. McInerney and McInerney (2002) found that the development of distinction between past and future in children happen to be a work in progress in their early years and as supported by Piagatian research, extends well up to middle school and high school years.

McInerney (2004) also stressed upon the need to study the role of gender, parental influence, technology and spirituality on the future time perspective of the students. In this study the researcher mentioned two vital future perspective that students of the present generation could possible take. He distinguished the life spent by the children in past to be fairly predictable, with the uncertainty and fluidity experienced by the children about their future in this generation. In such situations, the students would either be too much concerned and get involved in securing future by relying on schooling or become too detached with the reality and become alienated.

Husman and Shell (2008) presented future time perspective as a multi-dimensional phenomenon and constructed a tool for measuring future time perspective, involving four dimensions namely, extension, speed, connectedness and value. Value is defined as “the willingness to sacrifice the present for the future. “The ability to plan for future, connect present activities with future outcomes and general thought for future consequences is defined as connectedness”. “The amount of time an individual has in his habitual time space” is defined as extension. Speed is operationalized as “the speed at which time seems to move” in an individual habitual time space.

Stanescu and Iorga (2015) found a positive relationship between achievement motivation and future time orientation in post graduate students of Romania. They also found positive association between future time perspective and self –regulation, bringing it within the umbrella of self regulated learning variables. Lyu and Huang (2016) constructed and validated a tool to measure the construct future time perspective in adolescents and young adults.

Peetsma, Schuitema and van der Veen (2012) in a longitudinal study lasting for four years, found a fall in future time perspective about school, professional career and self regulated learning lead to a decrease in academic delay of gratification in 701 secondary school students in Netherlands. Rise in the perspective about future involving leisure negatively correlated with development of delay of gratification in these students.

Bembenutty and Karabenick (2004) mentioned that the display of delay of gratification in studies by the students not only depends on the element of interest associated with the study, but also on the utility value, which is the value or the outcome that is expected to come on successfully earning high grades in studies, but is psychologically and temporally remote in time. This is how an association between delay of gratification a future time perspective of the student is established (Gjesme, 1979; Husman and Lens 1999; Klineberg, 1968; Lessing, 1968). ***Those who have shorter time perspective, look for instant gratification and students with longer time perspective display longer delayed gratification (Klineberg,1968).*** It was only after Bembenutty and Karabenick (1996) developed a tool to measure the academic analogue of delay of gratification and operationally defined the construct, did research begin to relate it with future time perspective. Both the constructs were found to be the aspects under self-regulated learning. Delay of gratification happens to be a function of an individual's future time perspective (Klinberg, 1968). Those students who have high future time perspective, psychological experience a given period of time to be less extended when compared to students with shorter future time perspective. For the former, the perceived utility value of the reward in future holds a high price and that is why they are ready to wait to attain it and hence display delay of gratification (Husman and Lens, 1999) Bembenutty and Karabenick's study associated academic delay of gratification with future time perspective and brought them under the umbrella of self regulated learning phenomenon.

Gjesme (1979) referred future time perspective as “an individual’s beliefs or orientation oward the future concerning temporarily distant goals”. He cited that future time perspective develops gradually from the childhood. The existence of need in a particular situation makes the individual experience the absence of something in present and hence looks for it either in past or in future, and in this way develops an orientation towards time. With the improvement in thinking abilities, there is extension in deeper time perspective. It is because needs evolve in humans within the framework of means and ends, which in turn call for planning of long term projects. Thus, future time perspective or orientation is associated with development of elaborated thinking abilities in humans for the satisfaction of certain need through planning, intention and performance of tasks.

When needs are not met, they become desires in the mind. These desires develop only when the individual realizes that they can be satisfied through activities later. The individual learns to deal with delay and becomes aware of the period of time keeping him away from the desire. It leads to the concept of expectation which is the difference between the present sense of absence and future gratification of the desire. In this way, the development of future time orientation in individuals is a component of three elements, namely, the motive which begins the orientation towards future, delay of gratification which teaches the individual to control reactions and impulses and to wait in present, and the ability to use symbols to form the concept of future.

Academic delay of gratification is a culture specific variable and hence the need to repeat research work on this variable and to verify its association with future time perspective under the ambit of self regulated learning (Bembenutty and Karabenick, 2003).

Zimmerman’s (2000) cyclical model of self regulation assumes that delay of gratification and future time perspective exist in the learner in the form of a series of decisions which are taken by him or her not merely due to the expectancy value of the tasks but on the basis of a self-regulatory feedback cycle.

Bembenutty and Zimmerman (2003) found that when students display self-regulation by framing their time and the environment of learning, the relationship between academic delay of gratification and future time perspective becomes more relevant than ever. There are contextual factors associated with future time perspective as the learners' conception of their future goals evolves and continues to exist within an interpersonal situation, where factors from the self, society, environment, motivation, and cognition play vital role to insecure the attainment of the goal along with its enactment. Individuals possessing a strong sense of future orientation have inclination to involve in behaviors which are oriented towards future, like planning and delaying gratification (Strathman et al., 1994; Qian et al., 2015).

Atkinson's (1958) theory of achievement motivation assumes each individual to possess the dual motives of approaching success and avoiding failure. However, individual difference exists with respect to the strength of these motives. They are defined as the abilities to expect pleasure or pain respectively in situations involving achievement (McCleland, 1955) and hence the element of future is associated with them. Individuals with the motive to approach success display longer future time orientation.

The construct time perspective is defined as ''the totality of the individual's view on his psychological future and psychological past, existing at a given time'' (Lewin, 1951, p. 75). The individual time perspective was described by Zimbardo and Boyd(1999) into five dimensions. They are past negative PN (repelling views of the past owing to experience of traumatic events), present hedonistic PH (seeking pleasure and taking risk, little concern for the future and high impulsiveness), Future F (general outlook towards future and striving for attainment of future goals and rewards, number of hours spent studying per week), and past positive PP (cherishing warm memories of the past).

Stolarski, Bitner and Zimbardo (2011) claimed to conduct first research work relating time perspective to emotional intelligence and included delay of gratification as the third variable. They mentioned that understanding and regulation of emotions effect our perception about present and future, help in reasonably balancing present pleasure and future consequences, along with resisting of adopting impulsive behavior under stress. ***Emotional attitudes especially within future time perspective dimension, play a vital factor in predicting behavioral outcomes in delay of gratification processes as they are closely associated with conscientiousness, impulse control and concern for future consequences.*** In this way, time perspective and emotional intelligence are related, but the directionality of the relationship is unclear. Also, their study found the relationship of future time perspective with trait emotional intelligence to be very less. Ability emotional intelligence did not relate with future time perspective at all, indicating that ability emotional intelligence is associated with those dimensions of time perspective which are experienced emotions like PN, PP and PF, instead of the behavior preferred in future like F and PH. These results were surprising even to the researchers. However, the researchers did mention the cultural reality of Polish subjects who were under harsh Nazi and Communist rules, which negatively influenced the ability of polish people to conceive future. Though the researchers admitted that delay of gratification was an essential feature of future time perspective, they found surprisingly weak relationship between these variables and emotional intelligence and failed to explain the reason in a study conducted in Polish context, and hence there is a pertinent need to conduct the study on these variables in other cultures.

According to Zimbardo and Boyd (2008), presence of delay of gratification in an individual is essential for the display of time perspective, as its absence can lead to the typical display of present-hedonistic dimension of time perspective. Mischel, Shoda and Rodriguez, (1989) presented the role of delay of gratification in the development of future oriented behaviors and attitudes in children. So, along with present hedonistic dimension, future time perspective dimension can be a significant predictor of delay of gratification.

Dorrenbacher and Perels (2015) while developing and evaluating an integrative trait model of self regulation, included volition into the model framework and presented a new conceptualization of this construct as a trait. In this context, they included future time perspective, procrastination and academic delay of gratification as its components owing to indication of high correlation among these variables by previous researches (e.g. Bembenutty and Karabenick, 2004; Sirois, 2014) within the ambit of self-regulated learning (Park and Sperling, 2012; Zimmerman, 2011). Sirois (2014) stated that students with future time perspective had less procrastination and Tuckman (1991) showed that it is difficult for procrastinators to let go of their gratification. In fact, Dewitte and Lens (2000) argue that future time perspective mediate the relationship between academic delay of gratification and procrastination.

The need to conduct research work on future time perspective in non-western countries aroused out of the fact that the theoretical underpinning of Piagatian research was mostly held in western countries (McInerney *et al.*, 1997, 1998a), necessitating the conducting of such studies multi-cultural contexts (McInerney, 2004). Also, Cross-validation of the factor structures is vital for the development and large scale acceptance of the scale and for confirming that the developed scale is not a product of singular characteristics of the sample used as representation in the study, lacking external validity (Floyd and Widaman, 1995)

1.3.1.3 Academic Procrastination

Klein (1971) coined the word procrastination from the two latin words, namely "pro" which means "in favor of" and "crastinus" which means "of tomorrow". According to Ferrari (1998), procrastination is "the purposive delay in the beginning and/or completion of an overt or covert act, typically accompanied by subjective discomfort". Steel (2007) defined it as "to voluntarily delay an intended course of action despite expecting to be worse off for the delay". In the both the definitions a distinctive feature emerges which is the deliberate delay of the task by its performer in spite of being well aware of the consequences.

According to Saiputra (2010), the best theory to explain procrastination is the Temporal motivation theory. This theory says that individuals defer the performing of a task if its utility value post performance is low at a certain point of time as per the perspective of the doer. The formula for calculating the utility associated with procrastination has components like time delay (duration to get results) and sensitivity to delay (inclination to quick rewards) in the denominator of a ratio,and, expectancy (success probability) and value (preference towards activity) forming its numerator

(Steel and Konig, 2006; Steel, 2007). According to procrastination gounded theory (Schraw, Wadkins and Olafson, 2007),lack of incentives, deadlines and unclear directions are the three conditions affecting procrastination. Here, lack of incentives is same as value, unclear directions parallel expectancy, deadlines is same as sensitivity to delay. In this way, both the theories concur on their descriptions of procrastination. From the standpoint of self-regulated learning, the expectancy component of procrastination is related to cognitive component of SRL, utility is associated with cognitive, affective and behavioral component, sensitivity is associated with behavioral component of SRL and the time delay component of procrastination is related to cognitive, affective and behavioral component of SRL.

There are several measures to evaluate this construct namely, the Solomon Rothblum Procrastination Assessment Scale for Students (1988), the Lay General Procrastination Scale (1986), the Choi and Moran (2009) scale and the most widely used Tuckman (1991) Procrastination Scale to find out procrastinators in academics. Its academic analogue is the academic procrastination construct and measures quantifying academic procrastination should be preferred over scales measuring general procrastination (McCloskey, 2011). Wolters (2003) related academic procrastination with other self regulated learning variables like self efficacy and goal orientation along with the usage of meta-cognitive learning strategies.

1.3.2 Motivational Beliefs

Schunk (1990) presented the theoretical framework for explaining the role of self efficacy and goal setting in self regulated learning using Social cognitive theory of Bandura (1986,1989). In the same research they mentioned the role of goal orientation citing the work of (Dweck and Leggett,1988). Anything an individual strives to achive is goal and changes brought in form goal setting.Students begin a task of goal attainment only with a goal and self efficacy associated with it initially. Observation, judement and reaction by self affect both the variables and a sense of satisfaction towards the progress of the goal, also bring in a feeling of capability of enhancing the skills. With the attainment of goal, self efficacy is heightened, leading to the setting of fresh and challenging goals. Later, Bembenutty (2011) conducted a research which united the variables of goal orientation, self efficacy and intrinsic motivation under one umbrella of motivational beliefs in the context of self regulated learning.

1.3.2.1 Goal Orientation

According to Dweck’s motivational theory (1989), goal orientation can be treated as a stable dispositional trait with individual differences existing in the subjects as per implicit theory of ability (Dweck, 1989; Bempechat, London and Dweck, 1991). This theory is the link between theory of ability and the two goal orientations. It says that a person’s own theory of ability gives rise to a “default” direction under the influence of which the person tends to act.

When a performance goal is taken, the subject displays his or her competence before an audience and gain acknowledgment or does not perform the task to avoid criticism. But, when a task is taken up with learning goal orientation, the intention is to gain mastery over it to better perform the task in future (Dweck and Leggett, 1988; Heyman and Dweck, 1992). Though the construct can be divided into learning goal orientation and performance goal orientation, the relationship of the former is stronger with academic achievement than the latter’s. Moreover, both the dimensions were found to be uncorrelated to each other (Nicholls et al., 1989, 1985; Thorkildsen, 1988). Dweck’s theory is based on the implicit theory of ability which states that a person gets directed towards performance goals owing to an entity theory of ability and gets directed towards learning goals due to an incremental theory.

1.3.2.2 Self Efficacy:

Zimmerman (1989) defined self-efficacy as the manner in which a person views his own ability to put in order and execute actions required to attain pre-determined performance of skill for specific tasks by citing Social cognitive theory (Bandura, 1986). Schunk (1991) defined academic self efficacy as “one’s convictions to perform successfully at designated levels”. The relationship of self efficacy with motivation and academic achievement was explored in multiple studies (Bandura and Schunk, 1981; Betz and Hackett, 1981; Pajares and Miller, 1994; Pintrich and De Groot, 1990; Schunk, 1982, 1983, 1984; Zimmerman, Bandura, and Martinez-Pons, 1992; Pajares, 1996; Multon, Brown, and Lent, 1991; Schunk's (1982, 1983, 1984)).Pintrich and De Groot (1990) related academic self efficacy to self-regulatory strategy use. Self-efficacy for self-regulated learning is defined as the perceived ability of a student to use different self-regulated learning strategies like self-monitoring, self-evaluation, selfconsequences, goal setting and planning, and environmental restructuring (Zimmerman et al., 1992; Zimmerman and Martinez-Pons, 1988). Zimmerman et al. found that self-efficacy for self-regulated learning and self-efficacy for academic achievement were positively related together. Also, self-efficacy for self-regulated learning and academic self efficacy correlated positively (Joo, Bong and Choi, 2000).

1.3.2.3 Academic Intrinsic Motivation

According to the Self determination theory of proposed by Deci and Ryan (1985), individuals naturally perform certain organismic activities and have integrative propensities towards these activities, which help them in the satisfaction of their needs, with the display of diverse activities all along. Three critical psychological needs which forecast the behavior and their related outcomes in individuals are autonomy, competence and relatedness. Based on these premises, SDT classifies motivation into three types namely, the intrinsic, extrinsic and amotivation.

Academic intrinsic motivation consists of those learning activities which a student does for sake of enjoying the pleasure and satisfaction that are associated for him with the mere participation in such a task. Such a kind of motivation according to Deci and Ryan originates from the internal requirements of competence and self-determination. Vallerand, Blais, Briere and Pelletier (1989) postulated that this type of motivation is in turn made up of three types, namely, Intrinsic motivation to know, intrinsic motivation towards accomplishments and intrinsic motivation to experience stimulation.

1.3.3 Emotional Self Regulated Learning Strategies

There is consensus among the researchers that emotions and their regulation play an important role in learning, however little theoretical and empirical work exists in the literature on this topic (Boekaerts, 2007). According to Efklides (2011), emotions can be observed and manipulated in order to reach pre-set goals. No work exists which tried to incorporate emotional regulation strategy into self regulated learning framework (Ben-Eliyahu and Linnenbrink-Garcia, 2012; Boekaerts et al., 2000; Pintrich 2004; Winne and Hadwin, 1998; Zimmerman, 2000).

Ahmed et al. (2013) presented two separate routes of evidences to explain the role of emotions in self regulated learning. They cited the studies in experimental social-psychology research by Ellis and Ashbrook (1988) which indicates that negative emotions have the potency to hijack the cognitive resources needed during the encoding of information in activities of comprehension, elaboration, organization and decision making. Positive emotions help in segregating the available information and organize it in better ways (Isen, 2004). They secondly mentioned that research carried out in descriptive and experimental educational psychology reveal that emotions can stop self regulation of thinking. For example, important information processing strategies, organization and elaboration are severely hampered by test anxiety. They are rather promoted along with critical thinking and metacognition under the influence of positive emotions like hope, pride and enjoyment (Pekrun et al., 2002).

An effort to include emotional regulation strategies into self regulation framework was done by Ben-Eliyahu and Linnenbrink-Garcia (2013) based on the theoretical basis of Process model of emotion regulation by Gross (2003) and empirical tools of measurement by Gross and John, (2003) and Nolen-Hoeksema et al., (1993). An important finding of their study that was emotional regulation strategies are employed more by the students when dealing with least favorite courses.

In a recent comprehensive empirical study to develop and validate an instrument to measure trait emotional self regulated learning strategies, Buric, Soric and Penezic (2016) developed an instrument with 37 items measuring eight dimensions of emotional regulation strategies in academic context for high school and university students, based on Process model of Gross (1998) in a 5-point Likert scale, with responses ranging from1 to 5, where 1 is strongly disagree, 2 is disagree, 3 is neither agree nordisagree, 4 is agree and 5 is strongly agree. These eight dimension are situation selection, developing competence, redirection attention, reappraisal, suppression, respiration, venting and social support.

The process model of emotion regulation says that there are five families of emotional regulation processes which can be further classified into either antecedent focused or response focused based on their triggering before or during the emotional event respectively. The antecedent focused processes are situation selection, situation modification, attentional deployment and cognitive change. The fifth process of response modulation falls under response focused type of emotional regulation strategy.

Situation selection happens in the initial stages of emotional regulation and involves doing an act which lands the subject in a situation to feel an emotion for certain. Situation modification as the name suggests, involves changes the characteristics of the situation that provoked a certain kind of emotion in the subject. Attentional deployment family of emotional self regulation tries to change the attention course of the subject to influence his/her emotion. Cognitive change strategy involves changing one’s way of thinking about a situation or the way of managing the situation. Finally, response modulation family of emotional regulation strategy consists of processes which strive to change the bodily or the behavioral responses of the subject during the emotional experience.

The study found all the eight emotional regulation strategies to be related to certain unpleasant academic emotion. This finding is owing to the fact that emotional regulation strategies are primarily employed by students to deal with unpleasant academic emotions.

The scale developed by the researchers needs validation with respect to age group, educational level and culture or country as mentioned in the limitations of the study (Buric et al., 2016). This study needs further validation in global context and in Indian context in particular.

Though there are three commonly studied types of emotional self-regulation strategies in the psychology literature, namely, reappraisal, suppression and rumination (Aldao et al., 2010; Ben-Eliyahu and Linnenbrink-Garcia, 2016), in the proposed framework, the two dimensions, reappraisal and suppression, can be included since they were extensively studied already compared to other dimensions and for model parsimony. Engelmann and Bannert (2019) also mention that most of the research on emotional regulation strategies focused on expressive suppression and cognitive reappraisal. The cognitive reappraisal invoves giving a new meaning to an emotional stimulus so that its impact is changed (Gross, 2015). In academics, cognitive reappraisal in its specific form involves change of student's control and value, which is subjective in nature (Boekaerts and Pekrun, 2016; Jarrell and Lajoie, 2017; Pekrun, 2017). The Control value-theory (Pekrun, 2006, 2017), states that the academic emotions originate in students from the way they judge their competence and ability to master a learning task (control), and the way they judge their own importance or relevance in the learning activity (value). The subjective value can be both intrinsic like value of learning for the sake of it or extrinsic like rewards from learning, like good grades (Pekrun, 2006, 2017). Research studies have shown again and again that that cognitive reappraisal is positively related to emotional state (Jacobs and Gross, 2014; Webb, Miles, and Sheeran, 2012) and learning outcome (Davis and Levine, 2013; Strain and D'Mello, 2015), whereas the dimension suppression is negatively related to both these aspects.

1.3.4 Behavioral Self Regulated Learning Strategies

Wolters, Pintrich and Karabenick (2003) mentioned regulation of overt behavior of an individual as a self regulation strategy which can be observed, monitored, controlled and regulated, and thus is consistent with the triadic model of social cognition (Bandura, 1986; Zimmerman, 1989). In academic context, they elaborated that students can behavioral regulation during the time and effort they place while studying, by managing the time effectively by scheduling it and also the selection of conducive study environment. They explained that the subscales of effort regulation, help seeking and time and study environment in MSLQ were developed to measure this component of self regulation learning. They also reflected on their own previous study where these sub-scales where found to display independent existence as factors during factor analysis exercise in comparison of cognitive and metacognitive strategies (Pintrich etal, 1991,1993). They recommended the use of these subscales for the measurement of behavioral component of self regulated learning strategies.

The relationship of behavioral self regulated learning strategies with motivation and academic adjustment using the resource management section of MSLQ was later conducted by Cazen and Anitei (2010).

According to Cazan (2013) SRL is appropriate particularly for university students along with high school students, owing to the ability to control their time schedule, as cited by Pintrich (1995). Self regulated learning involves several types of strategies, namely the cognitive, metacognitive, motivational and behavioral components. While the cognitive strategies component is directly involved in the construction of knowledge, the rest of the strategies help and manage the learning process. Cazan (2012a) mentioned that MSLQ consists of 15 scales under motivation and learning strategies sections. While motivational section measures value, test anxiety and expectancy, the learning strategies section measures cognitive, metacognitive and behavioral self learning strategies. Cazan (2012b) listed the variables of resource management component, namely, time and study environment management, effort regulation, peer learning and help seeking, to be representing behavioral self regulated learning strategies, citing Pintrich et al. (1991).

The researcher used the 4 items of time and study environment of the revised MSLQ by Jackson (2018) to represent behavioral self regulated learning in the revised integrative trait model. Time management involves the student's study time schedule, plan and management. Environment management consists of selecting a place of study which is quite, organized and immune from any distraction. The other variables under this component, like effort regulation, peer learning and help seeking are not chosen owing to the inability of their scales to display good psychometrics in multitudes of validation studies of MSLQ in several cultures across the world.

1.3.5 Metacognitive Learning Strategies:

Metacognition refers the capability of an individual to comprehend, manage and ponder about one's own learning. It is made up of two components, namely the knowledge about cognition part and the regulation of cognition part. The former deals with the reflective aspect of metacognition, whereas the latter addresses the understanding and controlling of it. In the present research, the focus is on the latter aspect of metacognitive regulation strategies (Schraw and Dennison, 1994).

There are five component skills which are studied extensively to cover the regulation aspect of metacognition. They are planning, comprehension monitoring (self-recording), information management strategies, evaluation and debugging strategies (Baker, 1989; Artzt and Armour-Thomas, 1992).

Dorrenbacker's model (2015) included the components planning, self-recording and self-evaluation to represent the metacognition component of self regulated learning. As a part of replicating the previous research, the researcher would use the Metacognition Awareness Inventory by Schraw and Dennison (1994) to measure these selected components. In this scale, the operational definitions of planning includes activities like setting of goals and allocation of resources before learning, monitoring means assessing one's learning or use of strategy and evaluation implies analysis of one's performance and effectiveness of the applied strategy after learning. There are 7 items to measure planning, 7 items to measure monitoring (self-recording) and 6 items to measure self evaluation. Though the original scale records the responses as true or false, the researcher administered a 7 point likert scale on the items to record more graded responses.

The MSLQ scale, or the revised MSLQ scale by Jackson (2018), in its metacognitive self regulation sub-scale, blended the 12 items and 6 items respectively, under planning, monitoring, evaluation and debugging strategies and the items cannot be distinguished component-wise. Hence, it was considered in this study.

1.3.6 Cognitive Learning Strategies

According to Sungur and Güngören (2009) and Zimmerman, Bandura and Martinez-Pons (1992), structural relations among specific variables of self regulated learning strategies use to academic achievement can be studied independently apart from studying the use of these strategies of self regulated learning as a whole, on academic achievement. As a result, Sadi and Uyer (2013), studied the influence of cognitive self regulation strategies like rehearsal, elaboration, organisation and critical thinking on academic achievement.

All the strategies employed by a student to gain the understanding of a learning material comprise the cognitive learning strategies. They state the ability of individual to learn how to learn and play a vital role in all educational systems (Warr and Downing, 2000). Woletrs (1998) defined cognitive self regulated learning stretegies as one that helps the learners in becoming more successful by the usage of a strategy of learning. Research studies by Ning and Downing (2010), Sungur and Güngören (2009), Cekolin (2001), and Warr and Downing (2000) found that students who used cognitive self regulated learning strategies achieved better academically than those who did not use these strategies.

The acts of reading aloud and highlighting or underlining, recitation, along with other such acts form Rehearsal strategies which make students focus in the material, segregate vital learning material and commitment them to memory (Pintrich, 1999). According to Weinstein and Mayer (1986) when students take notes, create examples of their own, summarize, explain ideas and ask questions, they display Elaboration strategies. They also mentioned that when students manage to distill the main idea and put all its aspects in a proper order using different techniques, they show Organisational strategies. According to Paul (1992), critical thinking is defined as "an important process to shape and evaluate decisions about definite circumstances". Learning most importantly must accompany examination, critical analysis, drawing conclusions and making regressions. In totality, these strategies yield students with an ability to manage and give direction to their own learning (Pintrich, 1999). Sungur and Gungoren (2009) stated that students who are highly motivated to regulate their thinking and effort of learning make use of cognitive self-regulated learning strategies.

Dorrenbacker's model (2015) included the components critical thinking and organization to represent the cognition component of self regulated learning. As a part of replicating the previous research, the researcher used the MSLQ-R scale by Jackson (2018) to measure these selected components. In this scale, the operational definition of critical thinking is "the degree to which students report applying previous knowledge to new situation in order to solve problems, reach decisions, or make critical evaluations with respect to standards of excellence"(Pintrich, 1991). The operational definition of organization is “the ability to select appropriate information and also construct connections among the information to be learned“ (Pintrich, 1991). There are 4 items each to measure critical thinking and organization in MSLQ-R scale by Jackson (2018) with the responses recorded in 7 point likert scale, used in the present study.

Table 1.3 The SRL Domain's Heuristic Framework							
Construct	**Bandura (1977, 1991)**	**Carver and Scheier (1981, 1990, 2000)**	**Frese and Zapf (1994); Hacker (1985)**	**Kanfer and Ackerman (1989)**	**Locke and Latham (1984, 1990, 2002)**	**Pintrich (2000)**	**Zimmerman (1990,1996, 1998, 2000)**
Regulatory agent: Goal Level	✓	✓	✓	✓	✓	✓	✓
Regulatory Mechanisms: Planning		✓	✓		✓	✓	✓
Monitoring		✓	✓	✓		✓	✓
Metacognition			✓	✓		✓	✓
Attention		✓		✓	✓		
Learning Strategies						✓	✓
Persistence	✓	✓	✓	✓	✓	✓	✓
Time Management						✓	✓
Environmental Structuring						✓	✓
Help Seeking			✓			✓	✓
Motivation	✓	✓	✓	✓	✓	✓	✓
Emotion Control				✓		✓	
Effort	✓	✓	✓	✓	✓	✓	✓
Regulatory appraisals: Self evaluation		✓		✓		✓	✓
Attributions	✓	✓				✓	✓
Self Efficacy	✓	✓		✓	✓	✓	✓
Note: The ✓ indicates the presence of the construct as a component of self regulation is suggested by the theory							

Ideally, a framework of SRL is expected to be comprehensive, internally consistent and parsimonious (Austin and Vancouver, 1996). Though SRL theories are extremely broad, seven of the most significant theories refer to 16 main constructs that are responsible for learning mainly in higher education level, and the frameworks of Pintrich (2000) and Zimmerman (1990,1996,1998,2000) cover most of the these vital SRL constructs.

1.4 Need of the Study

According to the global report (2016) published by the Centre for Economics and Business Research, the Royal Academy of Engineering, London, the profession of engineering plays a vital role in the economic progress and improvement of the quality of life of the citizens of a nation, globally. A country's engineering capability measured through its engineering index, was found to be positively and significantly correlated to the gross domestic product GDP per capita and the investment per capita. The engineering index estimate comprises of the components like engineering businesses and wages, exports, employment, graduates, quality of infrastructure and the genderbalance in this profession. India's engineering index was measured to be 43% in the global standing. The study's main finding was that those countries which try to improve their engineering infrastructure industrially and increase their engineering graduates academically, have higher chance of experiencing significant economic growth.

Also, evolving research indicates that education in the fields of science, technology, engineering and mathematics (STEM) forms a better estimate of human capital as it takes into account the importance of education that propels innovation and generates workers who drive and take the technology forward, which is at the center of economic prosperity (Croak, 2018). Among the STEM fields, engineering is the most important one (Rothwell, 2013).

In India, the engineering sector, with its close link to the manufacturing sector, is of strategic importance to the country's economy, according to the Indian Engineering and Capital Goods Industry Report, (April, 2020), released by the India Brand Equity Foundation (IBEF), a trust formed by the Department of Commerce, Ministry of Commerce and Industry, Government of India, with the main objective to promote and create global awareness of the Made in India brand in foreign markets and to provide a platform tospread knowledge of Indian services and products. According to Debnath and Shankar (2012), the impact of engineering education sector on skilled labour market is profound, and hence it plays an integral part in the economic development of the country.

Trading on these lines, for boosting the Indian economic growth, one of the ways to increase the number of engineering graduates is by producing quality professionals from higher education universities and apex body approved engineering institutions, who remain committed to the ethics and demands of the profession by being life long (Guest, 2006) and self regulated learners (Odinokaya et al., 2019). According to Luftenegger et al., (2015), the very definition of life long learning involves self regulated learning as it is defined as “the competence for learning throughout one’s lifetime, a domain-specific competence that requires motivation and self-regulated learning”. In this way, lifelong learners are motivated and self regulated (Ng, 2016).

Since 1991, when India opened its domestic markets for foreign investments and embraced liberalization and followed by globalization (Nayak et al., 2005), there has been a period of rise in the demand of qualified manpower from the industry, causing exponential increase in not only the number of student enrollments but also in the number of engineering institutions (Upadhayay and Vrat, 2013a; Kovaichelvan, 2014). Galustyan et al., (2018) mentioned that one of the goals involving the training of professional specialists like engineers in engineering institutions is to provide students a strong basis of the fundamental knowledge, using which they can train themselves independently after the university. In this context, they stressed that such a target can be achieved by promoting self regulated learning in the students. Hawe and Dixon (2016), Ruiperez-Valiente et.al.(2016), Rutherford (2017) and Skinner et.al (2015) found that the promotion of self regulated learning in professional courses students should be initiated for sparking the requirement for self-education, for the usage of the acquired knowledgeand skills during professional training in a creative manner, to apply it on commencing professional practice andthereafter develop a sense positive motivation for improving professionally. The role of self regulated learning in professional education like engineering education is further placed in a solid ground by the works of Bergem (2016), Lin et al. (2016), Pedrosa et al. (2016), Schünemann et al. (2017) and Tio et al. (2016) in recent times.

Also, there is a trend of high rate of dropouts in the first semester and academic failure in the engineering program (Acevedo, Torres and Tirado, 2015; Garcia-Ros et al., 2018). This is due to lack of display of learning autonomy through self regulated learning by these students during their transition from high school to university. The solution for this inability of the first year engineering students to display the academic skills for graduating into the next year of study leading to low retention rates, rests in self regulated learning McCord, (2016). In the succeeding years, as high as 80 percent engineering students apply poor self regulated learning strategies during the course of study which badly affects their academic performance (Wisland, Duarte and Yoshikazu, 2014) leading to the production of poor quality professionals ultimately. Since self regulated learning can be taught (Azevedo and Cromley, 2004; Cleary et al., 2008; Schmitz and Wiese, 2006), higher education professional need to better understand how learners differ from each other in their self regulted learning capabilities and design customized intervention programs to study the varied effects these programs can have on the students (Hong and O'Neil, 2001), to make them academically independent and self regulated learners.

Moreover, India became a permanent signatory of the Washington Accord (1989) on 13th June 2014 (Mohanty and Dash, 2016), which is an elite international engineering studies agreement according to which the undergraduate engineering qualifications recognized by India's apex body, the Nation Board of Accredation (NBA) of AICTE established in 1994, will also be recognized in other signatory countries like Korea, Russia, Malaysia, China, South Africa, New Zealand, Australia, Canada, Ireland, Hong Kong, Taipei, Singapore, Srilanka, Japan, the United States, Turkey, United Kingdom, Pakistan and Peru, for ensuring mobility of qualified engineers among the signatory nations. The last and the 12th element of an engineering graduate's attributes [defined as "the qualities, skills and understandings a university community agrees its students would desirably develop during their time at the institution and, consequently, shape the contribution they are able to make to their profession and as a citizen", Bowden et al., (2000); Nair, Patil and Mertova, (2009)], according to this accord, WA-12, is that he or she should be a self regulated and life long learner, as quoted below from the report:

"WA12: Recognise the need for, and have the preparation and ability to engage in, independent and life-long learning in the broadest context of technological change".

- Pp:15, The Washington Accord Graduate Attribute Profile,
- 25 Years Washington Accord (1989-2014).

Development of self regulated strategies at university level for preparing the students to meet the demands of autonomous learning later in life, is thus the need of the hour (Capote, Rizo and Bravo, 2017). Though schools and universities are no more providing the knowledge and skills required for an individual for life, the foundation of lifelong learning is laid during initial training in schools and universities, which continue on the fly when individuals join the work force and have multiple jobs during their work career (Mawas et al., 2017). These informal and incidental forms of learning are self regulated in nature and make the most of the lifelong learning outcomes outside the formal settings of schools and universities as per adult education research (Trembley, 2003). It is during these times when individual become autonomous and take charge of their learning for life, becoming self regulated. Knowledge of self regulated learning strategies to the educators of university for instilling them in their students, then becomes critical, which comes from research on this subject. High achieving students use more self regulated learning strategies than low achieving students (Pintrich and De Groot, 1990; Van Zile-Tamsen and Livingston, 1999). However, research on the topic of self regulated learning in the domain of engineering education is in its early stage globally **(**Nelson, Shell, Husman, Fishman and Soh, 2015; Saez et al., 2020**)**, leave alone India's status of research in engineering education, where their scarcity of work (Sahu et al., 2013).

Though research on self regulated learning by treating it as a state is picking importance and pace (Azevedo, 2014), the individual differences of this construct in students can be studied by treating it only as a trait (Dorrenbacher and Perels, 2015). The trait approach of SRL in turn helps to validate its relationship with academic achievement (Dignath et al., 2008), and promotion of lifelong learning (Bronson, 2000).

In India, the studies conducted on self regulated learning at school and university levels, focused on the relationship of its components like cognitive (Vanitha, 2016), metacognitve (Singh, 2017), motivation (Brindha, 2010), and motivational beliefs (Jahedi, 2007) independently, with academic achievement and other academic variables. The researcher failed to find any research work which tried to study self regulated learning empirically within a single framework. In this context, the state of the art, German trait integrative model of self regulated learning as proposed by Dorrenbacher and Perels (2015) required validation in the Indian context. No study until now was reported in the Indian context which tested this existing international holistic model of self regulated learning and addressed the appeals of the foreign investigators to validate it in local context (Panadero, 2017). The behavioral component of SRL needed inclusion and validation, along with the trait emotional regulation strategy proposed by Buric et al., (2016) into this integrative framework, for the model to be consistent with the latest status of the theory of self regulated learning, which now mentions that SRL's components are cognitive, metacognitive, motivational including volitional, behavioral and emotional in totality.

The present study primarily addressed these concerns and contributed to the existing literature by revising the comprehensive or integrative model of self regulated learning, through the addition of two left-over SRL components as per theory, the behavioral and the emotional components into the model of Dorrenbacher and Perels (2015). The availability of such a comprehensive empirical SRL instrument was hoped to advance Engineering education in the country through estimation of individual differences of trait SRL and preparation of customized intervention programs, in future, as per the SRL profile of the engineering undergraduates.

Finally, the measurement invariance testing of the proposed model with respect to gender, batch and stream groups as needed for establishing the psychometric equivalence of the proposed SRL model across these groups and for comparison of SRL group means (Putnick and Bornstein, 2016), was performed on the students of second and third years of two prominent undergraduate branches of Engineering program(the AISHE report, 2019), Computer Science (with 5,27,252 enrolled boys and 3,53,097 enrolled girls) and Mechanical engineering (with 7,42,572 enrolled boys and 40,207 enrolled girls).

1.5 Significance of the Study

Table 1.4 Timeline of the Developments in the Research of the Construct SRL

S.No.	Stage of Development Description	Researcher (s)	Contribution
1.	Within Metcognition	Zimmerman (1986)	Provided a unique status to SRL
2.	Tool Development	Pintrich (1992)	Made the measurement of SRL components like cognitive, metacognitive, motivational and behavioral, possible.
3.	Integration of the components Metacognition and Motivation	Hong and O'Niel (2001)	Attempted to present the first empirical and integrative model of SRL
4.	Volitional Research	McCann and Garcia (1999) and Bembenutty and Karabenick (2001)	Made the empirical testing of motivation into choice and execution types, and lead the emergence of volitional components of SRL strategies
5.	Integration of three main components of SRL	Dorrenbacher and Perels (2015)	Integrated the cognitive, metacognitive, motivational along with volitional components of SRL strategies into the latest empirical model
6.	Emotional regulation strategies research	Buric et al., (2016)	Developed a comprehensive tool and lead to the measurement of trait academic emotional self regulation strategies
7.	Present Study	Researcher (2021)	Integration of all known components of SRL as per theory into an empirical model and measurement invariance testing of the proposed model with respect to gender, batch and stream

The existence of a theoretically comprehensive and empirically robust instrument can allow the measurement of individual difference of self regulated learning capability in subjects from multiple domains. The availability of such an information of profiles of SRL can prove handy in the preparation of customized intervention programs for students of multiple disciplines. In this way, evidence based promotion of SRL in universities and educational institutions can commence.

In all the above mentioned exercises, questionnaires as indispensible tool for measuring traits (Dorrenbacher and Perels, 2015) were used.The instruments to measure the volitional components of SRL like procrastination and future time perspective in the model were of foreign origin along with other tools, and as per the Indian context needed validation during their adoption owing to the cultural sensitiveness of the studied variables (Yasir, 2016). The adaptation of foreign origin tools has benefits like saving of cost and time when compared to construction of new tools from scratch (Gjersing, Caplehorn and Clausen, 2010). Hambleton (2005) expected test adaptations to become a common practice, owing to the exchange of tools from foreign origin, leading to an upsurge in the cross-cultural research.

Also, the concept of scale purification (Churchill, 1979; Frohlich, 2002) during adoption of foreign origin tools was introduced in this study. Its justification on the grounds of improvement in psychometrics of the tool and compliance with parsimony principle was presented. Scale purification becomes essential in the context of reflective constructs because their indicators are mere reflections of them. While the construct happens to be the independent variable, the indicators are the dependent variables and a possibility of elimination of the dependent variables without affecting the explained variance of the latent construct and enhancing their collective correlation arises here under measurement model of structural equation modeling (Jarvis et al., 2003).

Further, a gap in the literature of psychometrics was reported in the form of little awareness on the criteria to be adopted to remove items from an existing psychometric scale (MacKenzie et al., 2011, Hardesty and Bearden, 2004). This research study contributed psychometric works which demonstrated the application of little known criteria of item elimination during scale purification to the Indian psychometrics literature edifice. It would lead to improvement in the quality of the home-made psychological variables measuring instruments, and would bring transparency in the reporting of the statistical results in future studies.

Moreover, the psychometric evaluation of these tools, through selection of appropriate estimands of reliability, along with the parsimony verification of the tools was equally warranted (Wieland et al., 2017).

Apart from providing the psychometric advantage of a comprehensive SRL instrument as mentioned above, other significances of this study, like exercises of measurement invariance, scale purification and reliability analysis through alternative estimation, along with their best practices are explained below:

1.5.1Introduction to Scale Purification Exercise:

The social sciences, primarily deals with the study and analysis of latent variables defined as "phenomena of theoretical interest which cannot be directly observed and have to be assessed by manifest measures which are observable" (Diamantopoulos et.al, 2008). Such processes happening at the micro-level can be well-captured by self-report instruments like questionnaires conducted through survey techniques (Winne and Perry, 2000; Winne et al., 2001) and are considered to be indispensible (Dorrenbacher and Perels, 2015).

The concept of scale purification (Churchill, 1979; Frohlich, 2002), finds its place of introduction at this juncture as the technique based on which parsimony principle based shorter versions of questionnaires are developed to make them practical administratable on multiple sample subjects. Moreover when the studied construct is reflective in nature, while it is independent, the items or indicators representing it are dependent. Their elimination, without affecting the explained variance is essential for the development of parsimonious measurement models (Jarvis et al., 2013). This exercise is carried out under the name scale purification by calculating certain estimates from the obtained data and comparing them with their benchmark values as per classical test theory and item response theory. Little awareness exists on the criteria to be followed to remove items from an existing psychometric scale (MacKenzie et al., 2011, Hardesty and Bearden, 2004).

1.5.1.1 Estimates for Scale Purification:

The state of the art literature on scale purification mentions that the exercise is determined by the estimates of three facets, namely, reliability, validity and parsimony (Netemeyer et al., 2003, p. 57; MacKenzie et al., 2011). A brief description of these estimates and their benchmarks based on the Classical test theory are described below:

1.5.1.2 Classical Test Theory based Estimates:

i. **Inter-item Correlation for Parsimony:** According to the classical test theory, the observed score is a mixture of the true score sought after and the inevitable measurement error that creeps into it. The items to be removed from the original scale measuring the true score of a construct are decided by the measurement model under consideration, the most obvious of which is the domain sampling model which states that "the purpose of any particular measurement is to estimate the score that would be obtained if *all* the items in the domain were used" (Nunnally, 1967) represented statistically through the infinitely large correlation matrix. However, inclusion of all possible items is practically not possible leading to measurement error. The average correlation of this matrix then represents a common core of items through its dispersion. The key assumption of domain sampling method is that all the items, provided they belong to the domain of the concept, share equal portions of the common core. Thus, it implies that the items belonging to the common core would essentially represents all the items representing the construct itself (Ley, 1972; Nunnely, 1967), with responses of these common core items highly interrelated. For all practical purposes, items possessing inter-item correlation of above 0.4 can be retained.

ii. **Measure of Internal Consistency for Reliability – Cronbach's Alpha:** According to Nunnally (1967), "the square root of coefficient alpha is the estimated correlation of the k-item test with the errorless true score of the measure". This statement itself is sufficient to place the importance of reporting this estimate in the exercise of scale purification, provided the assumptions of tau-equivalence are satisfied (Raykov, 1997; Green and Yang, 2009; Teo and Fang, 2013). Items which reflect a factor should together produce an estimate of internal-consistency above 0.7. There are several alternative estimates of reliability which need to be reported in the place of the Cronbach's alpha depending on the nature of the data in realistic conditions like non-normality and ordinal nature of the responses in the scale. In the former case, robust alpha can be reported and in the later case, polychoric alpha can be reported using the freeware R/RStudio.

iii. **Confirmatory Factor Analysis for Validity– Factor Loadings:** The prevalent estimate to report construct validity is confirmatory factor analysis which involves evaluating the goodness of fit of the factor structure of a construct with the obtained data's pattern. The measures of goodness of fit can be broadly divided into absolute, comparative and parsimony goodness of fit indices, which when met, establish construct validity for the measured construct. These indices are in turn produced based in the regression correlation coefficients of the items with the factor to which they belong. The more an item is competent in capturing the factor it belongs, higher would be the estimates known as factor loadings. Items with poor factor loadings below 0.4 should be removed.

iv. **Goodness of Fit – Chi-Square Test:** Also, a non-significant Chi-square test result between the CFA results of the original and the parsimonious models, implies that there is not much of a significant difference between the two models, underpinning the exercise of scale purification.

v. **Increased AGFI of the Parsimonious model:** Furthermore, another indicator of a better parsimonious model is provided by the estimate AGFI. Usually, parsimonious models have higher GFI estimate but not the AGFI. If a reduced scale model has both GFI and AGFI higher than the original scale, it is an indication that the latter model is better one justifying the removal of the chosen items.

vi. **Increased Total Variance Explained:** The explained variance of the construct by the reduced items should have an equal or more, of the same estimate for the original set of items. This implies that the chosen items together explain fair amount of change in the construct of interest. This estimate can be found through exploratory factor analysis.

For multi-dimensional second order constructs, it is essential that the estimates measuring the relationship of a dimension with the construct are also measured. This measure provides an idea of the contribution of a dimension in the measurement of the entire construct.

Researchers heavily rely on the statistical criteria mentioned above, during the exercise of scale purification. However, experts are of the opinion that, judgemental criteria be also taken into account.The apparent advantages of scale purification is that the administration of the tool on the subjects takes less time and effort for the subjects to fill and return to the investigator without compromising on the quality of the instrument. However, the process of scale purification should be initiated only the scale is validated using structural equation modeling technique of confirmatory factor analysis. The tool can be constructed or adaptive in nature. In either of the cases, it is necessary that the original scale’s factor structure is ensured to be statistically intact.

Also, Grain size is the number of constructs that an instrument engulfs within itself. The more the number of constructs an instrument measures, smaller is it grain size. Rotgans and Schmidt (2010) showed that the MSLQ tool can not only be used at a course specific or task specific level, but also at a general curriculum level (Lonka et al, 2004), with smaller grain size to measure dispositional self regulated learning strategies. Since the objective of the present study is to measure the SRL in the target population at a comprehensive level, the appropriate level of context of MSLQ usage here is the general curriculum level (Makinen, Olkinoura and Lonka, 2002). Moreover, Vermetten, Lodewijks and Vermunt (1999) found that learning context has little role to play on the adoption of learning strategies which are stable in nature.

Finally, the study also stressed on the need to consider parsimony principle (Netemeyer et al., 2003, p. 57) along with reliability and validity considerations (Min and Mentzer, 2004; MacKenzie et al., 2011) during scale construction or scale adaptation. Parsimony is defined as the least amount of necessary information regarding an item (Wieland et al., 2017).

1.5.2 Introduction to Measurement Invariance Testing Exercise:

Historically, measurement invariance entered the literature of psychometrics in 1960s (Struening and Cohen, 1963; Meredith, 1964). However, the statistical know-how of measurement was accessible to the research community around the turn of 21st century (Widaman and Reiss, 1997; Vandenberg and Lance 2000). According to Cheung and Rensvold (2002), "measurement invariance is a general term that can be applied to various components of measurement models". A measurement model consists of a construct, its dimensions or factors and their respective items or indicators. Measurement invariance testing is the statistical property of a measurement model which indicates that the same underlying construct is being measured across groups or across time. The definition of measurement invariance as provided by Davidov et al. (2014) is "a property of a measurement instrument, implying that the instrument measures the same concept in the same way across various sub-groups of respondants, (p.58)". It is basic requirement before means of a variable across groups are compared (Putnick and Bornstein, 2016). It can be broadly classified into two types. They are:

a. **Multi-group invariance:** Does the model hold across groups (e.g., males and females, child and adult participants). In the present study, these groups are gender, batch and stream.

b. **Longitudinal Invariance:** Does the model hold across time (e.g., pre and post test), (Bialosiewicz, Murphy and Berry, 2013; Little, 2013; Widaman, Ferrer and Conger, 2010; Coulacoglou and Saklofske, 2017).

Longitudinal invariance testing require the evaluation the stability of an instrument across long duration of time and investment of money, time and effort. On the other hand, multi-group invariance tests can be conducted through cross-sectional studies in a comparitively easier manner.

There are two frameworks for conducting measurement invariance. They are Item response theory IRT framework (Tay, Meade, and Cao, 2015) and Structural equation modeling SEM framework (Widemann and Reiss, 1997). The SEM framework is more commonly used over the IRT framework (Putnick and Bornstein, 2016).

According to Little (1997), under the SEM framework of measurement invariance, there are category 1 and category 2 types of multi-group invariance tests.The former type, used in the present study, deals with the testing of psychometric properties of the measurement scales, and consists of hierarchically constraining tests called configural invariance (Buss and Royce, 1975; Irvine, 1969; Suzuki and Rancer, 1994), metric invariance (Horn and McArdle, 1992; scalar invariance (Meredith, 1993; Steenkamp and Baumgartner, 1998; Vandenberg and Lance, 2000), and measurement error or residual invariance (Mullen, 1995; Singh, 1995), and is the pre-requisite for conducting the latter type of study where differences in between-group differences with respect to their latent means, variances, and covariances are dealt. The details of the types of category 1 multi-group invariance tests are presented below:

1.5.2.1 Configural Measurement Invariance Testing:

A measurement model is said to be configural invariant when its factor structure does not change across subjects from two groups of interest, like gender (boys and girls), batch (Ist year and IInd year) or stream (Computer science engineering and Mechanical engineering). Once a factor structure is configural invariant, subjects from the two groups, look at the construct in a similar way (Riordan and Vandenberg, 1994). In both the groups, there will be same number of factors or dimensions for the construct and the items associated with each factor will also remain the same in both the groups (Meredith, 1993).When a measurement model does not come across as invariant in groups, it means that the subjects from both the groups understand the meaning of the construct in different ways (Millsap and Everson, 1991; Millsap and Hartog, 1988; Riordan and Vandenberg, 1994) or cultural context makes the construct appear abstract in nature (Tayeb, 1994) making its measurement a difficult task. Others reasons ascribed for failing of configural measurement invariance can be ascribed to problems associated with data collection, errors in translation of the items in the instruments etc. Until, a measurement model is configural invariant, no further invariance tests can be initiated. When this test fails, either the construct is assumed to be variant and discontinue the test or its definition is revised.

1.5.2.2 Metric Measurement Invariance Testing:

Once a measurement model is configural invariant, it is eligible for undergoing metric invariance testing. Here, the invariance of the responses of items across the group subjects is tested, that is, whether participants from the groups, respond to a specific item in the similar way or not. Statistically, it means that the factor loadings of the items must be same across the groups. That is, all the items in the instrument, measure their respective factors equally good in both boys and girls groups. When a measurement model is not metric invariant, the items of the scale measure the construct of interest to different extents. While an item would measure a factor of the construct in boys well, it may not measure the same factor of the construct in girls equally well, when it is metric noninvariant. As a result, the response for such an item by boys and girls would differ. According Bollen (1989), meaningful cross-group comparison of constructs is not possible without the instrument being metric invariant.

Practically, it is difficult to prove the tools to be metric invariant. As a result, there are group of researchers who opine that, items which are non-invariant in the tool, should be identified and removed, to be succeded by conducting of metric invariance test on the remaining items (Byrne, et al., 1989; Marsh and Hocevar, 1985). It is based on the reasoning that the removal of noninvariant items should not considerabely effect comparisons across groups to any meaningful degree, as the proportion of such items in the tool is small. When this test fails, the construct is assumed to be metric variant and further tests are discontinued, or tests of partial invariance are conducted by either removing or adding the constraints on the items loadings in a step by step manner and run the test, until partial invariance is achieved

(Jung and Yoon, 2016).

1.5.2.3 Scalar Measurement Invariance Testing:

When an instrument is metric invariant, it is eligible to undergo the next hierarchical test called the scalar invariance test (Mullen, 1995). Here, the intercepts of the items are tested for their stability across groups. The intercepts are item values or intervals with respect to the zero value of the instrument. When an instrument is found to be scalar measurement invariant, then its zero and intervals will be the same in both boys and girls groups. It is a prerequisite before the means of the latent construct in both the groups are compared.

Since achievement of scalar invariance is difficult, Byrne, et al., (1989) proposed fulfiment of partial scalar invariance where the noninvariant items are removed from the scale owing to their small proportion and effet on latent mean comparison, and the invariance testing is conducted again on the remaining items.When this test fails, the construct is assumed to be scalar variant and further tests are discontinued, or tests of partial invariance are conducted by either removing or adding the constraints on the items intercepts in a step by step manner and run the test, until partial invariance is achieved.

1.5.2.4 Residual Measurement Invariance Testing:

Measurment models are said to be residual measurement invariant, when their error variance associated with each item is same across the two groups. Error variance is that portion of change in the item which cannot be explained by the change in the construct and its associated factors of an instrument. Realistically it is not possible to prove an instrument to be residual invariant or error invariant, as the sources of measurement error differ from one item to another. One such source for the failing of residual invariance is when the subjects from a group are not aware of the instructions to follow while filling it when compared to subjects of another group, and fill the instrument in a haphazard manner (Mullen, 1995). Other reasons for residual noninvariance can be the grammer, vocabulary, syntax, idioms or cultural effects associated with the items (Malpass, 1977). When this test fails, the construct is assumed to be residual variant and further tests are discontinued, or tests of partial invariance are conducted by either removing or adding the constraints on the items residuals in a step by step manner and run the test, until partial invariance is achieved

According to Byrne et al., (2003), in cross-cultural research, from the definition itself, equivalency of the tested measurement model is established by proving its metric invariance. That is, it is enough if the construct means the same to subjects from both the genders and they understand the meaning of the items in the psychometric instruments used in the model, in same way. In the present study, the configural invariance of the structural revised trait model of self regulated learning among engineering undergraduates was tested across the groups based on gender, batch and stream.

The fit of goodness of measurement models is tested by comparing the hypothesized model with the observed data. Kline (2015) recommends reporting of multiple estimates during configural measurement invariance testing like Chi-sqaure, Root mean square error of approximation (RMSEA), Standardized root mean square residual (SRMR), Comparitive fit index (CFI) and Tucker-Lewis index (TLI). Since rest of the invariance test models are nested and are hierarchical in order, chi-sqaure test is conducted for testing goodness of fit of the preceeding and the succeeding models, which any significant difference in the models be directly attributable to the applied constraint on the item loading, intercept or residual respectively. The literature on the addressal of methodological issues on measurement invariance testing is still in the evolutionary stage, with little consencus among the researchers on aspects of its testing like number and order of tests to conduct before reporting invariance or partial invariance, model fit estimation criteria etc. (Putnick and Bornstein, 2016). Since most of the psychological theories are formalized as quantative theories (Busemeyer and Diederich, 2010; Lewandowsky and Farrell, 2010), and since one phenomena often has multiple competing explanations, the need for model comparison or model selection arise at the first place (Vandekerckhove, Matzke and Wagenmakers, 2015).

Also, in the present study the test of invariance of the model under multi-group invariance, with respect to gender (males and females), batch (IInd and IIIrd year) and stream (Computer Science and Mechanical) consisting of comparison between two groups under a particular criterion is done. Such studies are quite prevalent in foreign contexts if not in India. However, invariance testing of a model among multiple groups simulataneously (to include all or major streams of engineering) is methodologically challenging and yet evolving (Kim et al., 2017), hence is beyond the scope of this research study.

Moreover, a key issue with using MI testing with many groups is the question of how to handle a large number of groups in the comparison. Multiple group confirmatory factor analysis (MG CFA) is commonly used for MI testing, ***but mostly for comparing two groups.*** There are disadvantages when it is used for comparing a large number of groups. The number of pairwise comparisons across groups on any measurement parameters exponentially increases as the number of groups increases and the chances of falsely detecting noninvariance (Type 1 Error) are elevated when such a large number of comparisons are performed (Rutkowski and Svetina, 2014).

Furthermore, poor model fit can be an issue when a model of exact invariance (identical measurement parameters across all groups) is specified (Asparouhov and Muthén, 2014). Model fit criteria suggested for MG CFA with two groups (e.g., ΔCFI $\leq .01$; Cheung and Rensvold, 2002) are often too stringent when the number of groups is large, such as 10 or 20 (Rutkowski and Svetina, 2014). It is because simulation studies revealed that with the increase in the number of groups in the study of measurement invariance, the ΔCFI lowered and the ΔRMSEA increased. As a result, the experts recommend less stringent cutoff values for invariance testing multiple groups. The choice of only two streams, computer and mechanical engineering, is concurrent with these methodological and practical issues of Multi Group Confirmatory Factor Analysis in testing MI across many groups and prevalent conventions.

An interesting aspect associated with measurement invariance testing is with respect to the sample size required in the study. According to Cheung and Rensvold (2002), since alternative fit indices are used for evaluation of the goodness of fit in measurement invariance in 80 percent studies, the sample size plays not much role here as, these alternative fit indices are less sensitive to sample size.

While a camp of researchers recommend Cheung and Rensvold’s (2002) criterion of ΔCFI <0.01 for model fit, other camp recommends Meade et al. (2008) stringent simulation based criteria of ΔCFI <0.002 best for model fit. Further studies are required for the experts of the field to come on one page regarding the acceptable criterion for determing the estimates of model fit with respect to measurement invariance.

1.5.3 Reliability Analysis through Alternative Estimation:

Contrary to popular beliefs, reliability is not a property of an instrument but a function depending on the sample on which the instrument is administered and hence needs estimation frequently (Guilford and Fruchter, 1978,p.431; Crocker and Algina,1986,p.131). The estimand reliability of these instruments is estimated using the infamous but popular point estimator Cronbach’s alpha (Socan, 2000). Instead, an alternative confidence interval reliability estimator called greatest lower bound or McDonald’s Omega should be estimated for SRL tools (Sijtsma, 2009). Otherwise, to deal with reliability under realistic conditions, alternative estimates of reliability based on the ordinal and non-normality nature of the data must be reported (Gadderman, 2012). Also, reliability of the items in a scale and its overall internal consistency changes when used from one model to another (Chin and Marcolin, 1995). Borsa, Damasio and Bandeira (2012) provided the considerations to be taken care of when adapting tools of foreign origin in a local culture and steps to follow while validating it, as there is no consensus with regard to the step to be followed in this process. The study not only sought to address these pertinent issues by applying state of the art techniques of reliability analysis, but also tried to present a tutorial for administering these techniques. In this way, the research sought to contribute some psychological instruments for measuring vital self regulated learning variables in the Indian engineering undergraduates and proposed the means to estimate state of the art alternative statistical techniques.

1.6 Statement of the Problem:

The research problem is titled as “Measurement Invariance Testing of the Revised Integrative Trait Model of Self Regulated Learning among Engineering Undergraduates”. The researcher extended his earlier research studies of SRL variables (Chakraborty and Prabhakaram, 2015a; Chakraborty, 2015b; Chakraborty, 2015c; Chakraborty, 2016a, Chakraborty and Ahmed, 2016b; Chakraborty, 2016c; Chakraborty, 2016d; Chakraborty, 2016e; Chakraborty, Sulthana and Askari, 2016f; Chakraborty, 2016g; Chakraborty and Sultana, 2016h; Chakraborty, 2017a; Chakraborty, 2017b; Chakraborty, 2017c; Chakraborty and Chitra Lekha, 2017d; Chakraborty, 2017e), on volitional strategy variable academic delay of gratification and other variables of this category in learning environment, namely, procrastination and future time perspective (Steel, 2007) which are highly interrelated (Dewitte and Lens, 2000) and highly stable (Sirois, 2014). In this way, the validation of an integrated trait model of motivation component of SRL involving the new volitional sub-component of SRL and motivational belief sub-component has been studied in this research. This is an important step in replicating the latest empirical integrative trait model of SRL by Dorrenbacker and Perels (2015) in the Indian context. Such attempt is first of its kind in India and addressed the appeal to do so by several foreign researchers (Bembenutty and Karabenick, 2004).

This study also tried to validate the trait emotional regulation strategy (Buric, Sonic and Penezic, 2016) and a behavioral strategy component and integrate the same into the comprehensive trait model of self regulated learning (Dorrenbacker and Perels, 2015), since the theory of self regulated learning now states the presence of cognitive, meacognitive, motivational, volitional, behavioral and emotional components in it. This exercise is the first of the kind anywhere as per the knowledge of the researcher.

Finally, Measurement invariance (MI) testing study with respect to gender, a first of its kind in the Indian self regulated learning based research on engineering undergraduates, was planned to establish the effectiveness of the proposed SRL framework to be gender neutral. It is essential to obtain such a finding for the validity of the framework as it would be made a base for training interventions for the promotion of SRL at university level, through the comparison of its mean value across multiple groups. The relevance of MI can be argued in the context of the findings which state that girls are at greater risk of leaving STEM (Science, Technology, Engineering and Mathematics) courses than boys at all levels of education owing to the loss of interest (Ellis et al., 2016; Pelch, 2018) and due to the hegemonic masculine culture for leaving engineering (Silbey, 2016).

In total, the study compared two models of volitional strategy to integrate the better model into the motivational component of the Integrative trait model of self regulated learning proposed by Dorrenbacher and Perels in 2015. It then integrated the emotional (Buric et al.,2016) and behavioral (Cazen, 2012) components of self regulated learning into this comprehensive framework and finally validated the proposed trait based comprehensive SRL framework by establishing its measurement invariance with respect to gender, batch and stream to overcome the limitations of the Dorrenbacher and Perels (2015) work. These objectives of the study were achieved by selecting the second and third year engineering undergraduates of Punjab state of India.

1.7 Operational Definitions

1.7.1 Measurement Invariance Testing

It is "the statistical property of a measurement model which indicates that the same underlying construct is being measured across groups or across time, which is a basic requirement before means of a variable across groups can be compared".

1.7.2 Trait Self Regulated Learning

It is "a general disposition of students and learners involving relatively stable tendencies to use SRL strategies". These stable strategies belong to the components of self regulated learning, namely, cognition, metacognition, motivation (involving motivational beliefs and volition), emotion and behavior.

1.7.3 Engineering Undergraduates:

Engineering undergraduates in this study meant bonafide second and third year computer science and mechanical engineering students of UGC recognized universities and AICTE approved engineering institutions located in the three regions, Majha, Doaba and Malwa of Punjab state of India.

1.8 Research Objectives

1. To validate the trait model of emotional self regulated learning in the Indian context.
2. To validate the trait model of volitional self regulated learning in the Indian context.
3. To validate the role of trait volition in the revised integrative trait model of self regulated learning in the Indian context.
4. To validate the revised integrative trait model of self regulated learning in the Indian context.
5. To validate the measurement invariance of the revised integrative trait model of self regulated learning across groups, with respect to gender, batch and stream, in the Indian context.

1.9 Research Hypothesis

1. H_0: The revised integrative trait model of self regulated learning is measurement invariant or equivalent, with respect to gender, batch and stream, in the Indian context.

1.10 Delimitations of the Study

The study has been delimited as per the following aspects:

1. It is delimited to the engineering undergraduate students only.
2. It is delimited to the engineering undergraduate students from computer science and mechanical engineering branches only.
3. It is delimited to the engineering undergraduate students from computer science and mechanical engineering branches of IInd and IIIrd years only, of the Indian state of Punjab.

1.10 Brief Resume of Succeeding Chapters

The second chapter comprises of the state of the art regarding the research in self regulated learning among engineering undergraduates, the models of self regulated learning and on measurement invariance, concluding with the conceptual models of this research. In the third Chapter, the design of the research including the details of the population, sampling frame, sample, the tools used and the statistical tests employed are discussed. Chapter four deals with data analysis and interpretation.

In Chapter five, a discussion on the findings of the data, their educational implications, areas uncovered and untouched and conclusion are presented, succeded by a detailed list of References and Appendices.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

"If I have seen further than others, it is by standing upon the shoulders of giants."

-Issac Newton.

This quote aptly expresses the relevance of the predecessor investigators and the role of their findings in building the edifice of knowledge at any given point of time. The intellectural debt is paid by the successive researchers by undertaking the exercise of literature review and duly acknowledging the predecessor's works through proper citations and references.

According to Best and Kahn (2006), the exercise of literature review is taken up to show proof for the familiarity of the researcher with the already existing works and the unknowns in the field worth exploring. It removes redundancy and helps in formulation of viable hypotheses for the selected research problem. The exercise reveals previous studies which second our proposal and some studies indicate discretion and caution to observe in certain specific aspects of the study. Such disclosures enhance the insights of the researcher in the chosen area of study and provide him or her state of the art status as well. This further paves the way to take up meaningful research projects. However, only those studies which are absolutely relevant, done with competence and reported clearly should be included in the list of reviewed literature.

Some of the important aspects to be taken into account while conducting literature review are as follows:

- Reporting of only studies should be done which are intimately related to the research problem in hand.
- The methodology adopted, data collection means or instrucments and the manner of data collection.
- Details of the adopted Sampling design with mentioning of the population and criteria for the selection of the chosen sample subjects.

- Role of the independent, dependent and confounding variables in the study.
- Limitations of the study
- Recommendations for the studies to be taken up successively

By mentioning the above list details of the previous studies included in a literature review, the researcher ensures that the problem is well defined, its significance is well appreciated, efficient data-gathering tools are identified, relevant sources of data are identified and according a crisp research design is formulated.

In the succeeding sections of this chapter, the researcher provides the state of the art studies conducted in the last two decade, in the field of self regulated learning learning strategies among engineering undergraduates, to be succeded by research on the topic of trait based empirical models of self regulated learning and finally on the topic of measurement invariance statistical technique and its related aspects like the developments in the field of pscyhometrics with respect to the estimation of various estimates, estimands and estimators. Certain milestone studies owing to their historical relevance are also included. Discussions on each of these topics, followed by a summary, is presented about what the previous studies achieved, indicating the areas to be explored in the future studies, whose inclusion would justify the conception of certain conceptual frameworks of this research study. The chapter ends with the presentation of these conceptual frameworks.

2.2. Literature Review on Self Regulated Learning Strategies Based Research among Engineering Undergraduates:

Zimmerman (1990) presented a study which discussed about the three vital aspects comprising a general definition of self regulated learning. In this study, he also demarcated processes from the strategies of self regulated learning. While the former constituted the elements of the phenomenon, the latter represented avenues to enhance these components. Self regulated learning strategies were referred by Zimmerman in this study as “actions and processes directed at acquaition of information or skills that involve agency, purpose and instrumentality perceptions of learners.” The central feature in the general definition for self regulated learning was reiterated by him based on his previous study as “a systematic use of metacognitive, motivational, and / or behavioural strategies in the learning” (Zimmerman, 1989a) by the learners to achieve academic outcomes. Another vital aspect of the definitions of self regulated learning involved the concept of “self oriented feedback” loop (Carver &Scheier, 1981; Zimmerman, 1989b), where the student, as a part of a cyclic process, keeps track of the usefulness of the employed strategies of learning and work on the received feedback in covert as well as overt ways. The third aspect of the definition of self regulated learning, is the motive and mechanism behind the adoption of a self regulated learning strategy by students. Either rewards or punishment are behind the selection of the strategies as mentioned by operant theorists (Mace et al., 1989), or they are adopted to experience a universal sense of self-actualization as proposed by phenomenological theorists (McCombs, 1989).

In one of the initial studies exploring the role of self regulated learning in engineering education, Tynjala et al. (2005) studied the effects of the factors like learning environment and study orientation of 394 university students of Finland, pursuing engineering and selected through stratified sampling, on their academic success. The study conducted using questionnaire for measuring learning environment and study orientation and by collecting GPA for study success of the students, found that the way students perceived their learning environment effected their orientation towards studies, which in turn impacted their aacademic achievement. The students who displayed self regulation in their studies excelled well in studies, and those learners who relied on external factors and shallow strategies performed very poorly in academics.

French et al. (2005) found that academic motivation played an important role in the continuing of engineering education by the students, along with higher academic achievement in the first year of engineering and strong academic background. This study emphasized on the role of academic motivation in the student’s retention in an engineering program. The participants of the study were first year students of 2002-2003 academic years from Mid-western university of the United States.

Suresh (2006) primarily examined how the engineering students who performed well in the barrier or gate keeper courses persisted with the program in the later years. Factors like performance of the student in studies in school, behaviours like study habit, coping strategies, work habits, the perception students of the study held about faculty, culture of the engineering school and the presence of vital self regulated learning strategy, academic motivation, decided the performance of the students in engineering foundation courses. It found that most of students leave the engineering program in first or second year when they do not succeed in clearing the barrier courses of calculus, physics and statics. It also drew the attention of the research community towards the beliefs of the engineering faculty regarding these courses as the ones that remove or weed-out the ineligible students from the engineering program. Holding of such a notion also, acts as a roadblock for the students to pass these courses in the first attempt.

Kosnin (2007) studied the role of self regulated learning in the academic achievement of 460 students from the second year of electrical engineering program belonging to the UniversitiTeknologi Malaysia. The MSLQ instrument was used in the study to measure the extent of self regulation in the engineering undergraduates and GPA of the current semester of study was used to measure their academic performance. The study found a significant relationship between the two academic variables. Students from high academic achievement group differed from their counterparts in the low academic achievement group with respect to the use of SRL strategies. While resource management strategies and control of learning belief helped high achievers, meta-cognitive strategies proved handy to the low-achievers in their learning. This study through its findings stressed on the need of development of customized interventions programs for low and high achievers owing to their varied usage of SRL strategies.

Vogt (2008) addressed the issue of retention of the engineering program students and its factors, in the background of the usage of self regulated learning strategies. The study discussed the factors which contributed to students dropping from engineering programs before its completion and how the lack of commitment of the faculty in engineering education is one of the reasons. The role of the factors, faculty distance and academic integration were studied on self regulated learning variables of self efficacy, critical thinking, help-seeking and peer learning, along with academic confidence and academic achievement. Self efficacy, academic achievement and academic integration were negatively affected in the presence of faculty distance. Academic integration positively effectedself efficacy, efforts placed in study and critical thinking. 713 engineering students from multiple streams, belonging to the Institute of Electronic and Electrical Engineers (IEEE) and Society of Women Engineers (SWE), were the participants of this study selected using convenient sampling. The variables of self regulated learning were measured using MSLQ and GPA was the measure of academic achievement. The study applied Structural equation modeling or SEM to obtain the above mentioned results. SEM is defined as "allows examination of a setof relationships between one or more independent variables, either continuous or discrete, and one or more dependent variables, either continuous or discrete" (Ullman, 2006). It involves two steps, which are validation of the measurement model of interest dne through Confirmatory factor analysis (CFA) and fitting the structural model achieved through path analysis.

Baillie and Bernhard (2009) mentioned about the significance of simultaneous advancement of research in the theories and practices of engineering education, citing the works of Dewey (1983) way back in 1922.

Kolari, Savander-Ranne and Viskari (2010) studied the role of time and effort placed in studying engineering subjects by the students and the selection of a conducive environment on their knowledge and ability to solve problems. 54 first year engineering students from electrical and environment engineering streams were the participants of the study, which tried to find how much time these students place in learning activities and whether the placed time and efforts are in congruence with the requirements as per the curriculum. Only 3.7 percent students spent more than 30 hours/week on studies. Most of the students 37% of them studied only 6-10 hours per week. Over all, the students used 63% of the time allocated to studies as per the curriculum on average. The study was done in Finland and concurred with similar studies conducted in Europe in past.

Aswad et al. (2011) touched upon the need to bring changes in the policy and raise awareness on impact of negative stereotypes of engineering which restrict women from joining this field in the United Arab Emirates (UAE) as the country tried to become a knowledge-based economy. Semi-structured interviews and survey methods were employed to gather data from subjects pursuing science, technology and engineering (STEM) programs from 17 university campuses in UAE, belonging to the age group of 20-25 years. 50% of the participants said that personal inclination was the reason for them to take up the STE program. It suggests that women's participation in these programs can be imporved by simply providing them with more information regarding the future prospects of these programs.

Ramirez-Echeverry et al. (2011) validated the Columbian version of MSLQ scale in Spanish by administering it on 1218 engineering students and found it possess similar psychometric properties like the original study in English. The reliability estimate of internal consistency ranged from 0.58 to 0.92, and the construct validity was established through confirmatory factor analysis of the motivation and learning strategies subscales. The opinion of the expert judges was used to estimate the content validity of the tool. Overall, the MSLQ-Columbia is valid and reliable instrument to measure the SRL in undergraduates and is available for free through an email sent to the authors of the study.

Haron and Shaharoun (2011) studied the role of usage of SRL strategies in the performance of the foundational engineering course of Statics, considered to be a tough subject to pass, leading to dropping out from the program due to disheartenment. 131 students were surveyed and interviewed to find that their beliefs in learning and selection of learning strategies influenced their results in Statics course. Later, the study further investigated the role of SRL strategies on the results of Statics course. The Statics Concept Inventory and the MSLQ instrument were used to collect data of the performance of the students in statics and the presence of SRL strategies in them. While the sub-scales of MSLQ were the independent variables, the scores of Statics course were the dependent variables. Multiple regression analysis revealed that all the 15 sub-scales moderately and significantly predicted the Statics scores with 21% variance. Most of the students felt a sense of personal responsibility to pass the course through their efforts alone and by understanding the concepts of the course thoroughly. Among the variables of motivation scales, learning beliefs and self efficacy were the main predictors of performance and among the learning strategies sub scales, meta-cognitive regulation was the largest predictor of performance in statics course.

Anias et al. (2012) studied the cognitive and motivational strategies employed by 339 first year civil engineering students of Chilean University using the Motivated Strategies and Learning Questionnaire (MSLQ) with respect to the Introduction to Calculus course. The internal consistency reliability of 15 subs-cales varied from 0.45 for help seeking to 0.91 for self efficacy. Here, the students were found to possess high control of learning beliefs and task value as they employed motivational strategies. The cognitive learning strategies were slightly lower than the previous mentioned strategies, with high value of effort regulation and meta-cognition regulation. Both these strategies were found to be interrelated components and affected the learning outcomes of the participant students.

Lawanto and Santoso (2013) studied the usage of SRL strategies by 97 engineering students registered in the fundamental electronics for engineers course on academic achievement in the University of Utah, by maintaining enhanced guided notes. An instrument based on the SRL theory by Butler and Cartier was used to gather data on SRL strategies. GPA was used to measure academic performance. Cluster analysis was used as the statistical technique. The study found the intervention of maintaining the notes improved study grades. Students had profiles with respect to their SRL usage. High achievement group students made use of planning, monitoring and regulation strategies and the low achievement group students showed poor awareness of the SRL strategies.

Borrego et al. (2014) initiated writing of systematic reviews in the field of engineering education by reviewing 14 articles on the subject and presented its benefits like being a one stop point for finding the state of art in a particular field until the date of publication of that work for researcher in the pursuit of literature review. All the benefits of thorough literature review can be riped by researchers by accessing systematic and narrative review articles in one go. This research drew the attention of the scientific community towards the fact that engineering education did exist for 100 years (Lohmann and Froyd, 2010), but the research in this field was yet in its infancy stage, leave alone the mentioning of research on self regulated learning.

Nelson et al. (2015) conducted a study to find the role of motivation and self regulation constructs in completing the foundational courses of engineering program which play a vital role in the successful completion of the program itself. 538 students were participants of the study who were profiled based on the self regulated learning strategies adopted by them. Nearly 83 perent students who enrolled in these vital courses have poor profiles which severely impacted their learning. This study also mentioned a previous study (Budney et al., 1998) that low academic achievement in the foundational or gate keeper courses lead to student drop-out in the First year of engineering. Also, it cited the study (Veenstra, Dey and Herrin, 2009) that the grade point average of first year played as an indicator of persisting with the program and eventually completing it (Adelman, 1999).

Huzifah et al. (2016) conducted a study on 78 engineering students of the UniversitiKebangsaan Malaysia pursuing Circuit theory course for the academic year 2013 and 2014 to find out the extent to which these students used SRL motivation strategies in their learning using Pintrich and Zusho (2002) scale. They found that most of the students used conventional methods of learning like prepration a day before the exam and learning a subject merely to clear the examination. No efforts were placed by these students to grasp the content. Nearly 80 percent of the students had motivation of 3.5 in the seven point Likert scale, which implied that there is enough room for improvement of SRL strategies in the engineering students.

Van Den Broeck et al. (2017) discussed the theory of Input-Environment-Outcome by Astin (1993) in the context of the issue of high dropout rate of the first year engineering students and their retention. The input variable of this theory is the high school academic achievement. The output variables are academic achievement and retention. The environment variables are student’s academic experience in the university post admission. The output variables are dependent on the input and environmental variables. Also, the models involved in the study of the academic success of engineering students are different from the models which study the academic success of non-engineering students (Veenstra, Dey and Herrin, 2008).

García-Ros et al. (2018) tested a structural model in which the impact of the variables related to pre-university academic and social experiences were studied on the retention of the first and second year students in the engineering program. 243 first year engineering students of the academic year 2010-2011 were selected in this study. Path analysis statistical technique revealed that GPA of the first year and institutional commitment were found to be the best indicator of retaining the students in the program. The academic performance of the students at senior secondary level was found to effect the performance in the first year of engineering and indirectly effected the dropping out from the course or continuing with it. Also, the GPA of first year in engineering was influenced by variables like study preferences, integration and conscientiousness in studies.

Zhang et al. (2019) drew the attention towards the work of Alexander et al. (2011), who stressed on the need to conduct SRL research which is domain specific like engineering, as very few studies on this aspect exist. They discussed that Poitras and Lajoie (2013), Dym et al. (2005) and Dabbagh and Kitsantas (2013) showed the SRL strategies employed by students differ from one domain to another, furthering the need for conducting domain-specific engineering research. They also mentioned the findings of Cleary and Callan (2018) which found the Zimmarman Model of SRL (1990, 2008, 2013) to be apt for studying SRL both at general and at specific domain or task level. Using these previous works, this study's major finding was that there existed four kinds of behavior specific SRL profiles, namely, the competent, reflective, minimal and cognitive-oriented learners. The two extremities of the SRL learners, competent and minimal, represented two ends of self awareness of SRL confirming the previous findings of Zimmerman (2002) that students differ in the extent to which they are aware of SRL, which is inversely related to failure of SRL in them. It also found that task and mode of assessment of learning outcomes influenced the changes in the SRL processes taking place in the students. They too reported the presence of very few empirical studies of SRL in the field of engineering education and reviewed STEM related research works instead to increase their scope of study. However, the participants of this study were 108 nine-grade students enrolled in a foundational physical science honor class, where they were exposed to engineering design projects.

Saez et al. (2020) presented a systematic review of the empirical and quantitative research that took place on self regulated learning in engineering students. Articles with keywords “self-regulated learning”, “higher education” and “engineering” were used to find relevant articles frm the databases Web of Science and Scopus, belonging within the time period of 2007 to 2019. 21 articles were included in this study, comprising of 10 studies from the United States, 3 from Malaysia and one each from Mexico, Columbia, Brazil, Chile, Italy, Turkey and China. 13 studies were descriptive in nature, 4 of them used experimental design and 4 were of mixed research design. The sample size was as small as 15 to as high as 1218 in these 21 reviwed articles. 15 out of the 21 studies discussed the relationships shared by different variables under the umbrella of self regulated learning while 6 studies mentioned the interventions which can promote autonomous learning in engineering students. The instrument of choice in nine of the studies, was the MSLQ. This study discussed that when students from senior secondary stage, enter into the engineering program, the program demands learning autonomy and most of the students do not adapt successfully to this transition into a novel culture (Graffigna et al., 2014, Gale and Parker, 2014). This results in higher drop-out rates and academic failures in the very initial term of the engineering program (Acevedo, Torres and Tirado, 2015). The percentage of engineering students who cannot apply self regulated learning strategies in their studies and perform poorly in their academics is as high as 80 percent (Wisland, Duarte and Yoshikazu, 2014). Poor academic performance is inturn shown to be a strong indicator of dropping out from the program as discussed in the previous studies. The engineering students do not apply the meta-cognitive strategies like planning and monitoring (Zambrano, 2016) and increased levels of learning and development of SRL strategies in students are found to covary (Ernst and Clark, 2014). Research in the field of engineering education does not focus on the subject of self regulated learning (Jesiek et al., 2011; Borrego et al, 2015). The previous findings helped this study to disclose that research on the topic of self regulated learning on engineering subjects is at its initial stage of development.

Summary: Review of the available literature on the self regulated learning strategies research on engineering undergraduates, reveals that engineering education did exist for 100 years, but it is still in its infant stage, leave alone research on self regulated learning in engineering students. It was insightful to learn from a 2009 review that way back in 1922, the significance of simultaneous advancement of research in the theories and practices of engineering education was mentioned. The need to conduct research on this general and or domain specific topic is in the cognizance of the research community. Zimmerman's model of SRL (1990) was found to be apt for both the purposes. One of the initial studies on this topic was conducted in 2005 in Finland and established the relationship of self regulated learning strategies of engineering students with the critical academic achievement variable. However, subsequent studies were fragmented in the sense that they explored different components or aspects of self regulated learning in engineering students discretely using the MSLQ instrument. The high drop out rate of first and second year engineering students owing to the failure to pass the vital courses like Physics and Calculus, and their retention found its rightful place early on in the literature in 2006 although, along with the 2007 research on the need of development of customized interventions programs for low and high achievers owing to their varied usage of SRL strategies. Slowly but steadily, SRL research on engineering students is peaking pace in multiple nations of the world.

2.3 Literature Review of Empirical Research on the Models of Self Regulated Learning:

The empirical research studies based on the SRL models of Zimmerman, Boekaerts and Winne are included owing to the fact that their models are extensively used by scholars involved in the research of self regulated learning and these models consistently appeared in the handbook of self regulated learning as well (Panadero, 2017).

2.3.1Empirical Research Based on Zimmerman's Cyclic Model of SRL:

Zimmerman and Kitsantas (1997) studied 90 physical education girl students of 9^{th} and 10^{th} class with respect to their dart throwing ability. 10 students formed the control group which involved no self recording and no seeting of goals. Rest of the 80 students formed the eight conditions of testing in this experimental design study, with 10 members in each group. These eight conditions were process goal with self-recording, shifting goal with self-recording, outcome goal with self-recording, outcome goal but no self-recording, transformed goal with selfrecording, process goal but no selfrecording, shifting goal but no self-recording and transformed goal but no self-recording. The study used questionnaire to measure self efficacy, Intrinsic interest, self-reactions, attribution and test found to measure the dart throwing skills of the participants. The study was done to know the role of setting of goals and recording the self, when sportsmen try to gain a complex motor skill through the display of self regulation. The researchers found that participants who changed their goals from the process to the outcome as a part of organic development, performed well in comparison to those participants who focused only on the goals. The latter group was found to perform well in the comparison to the participants who focused only on the outcome. The way the sportmen react to the outcome of the dart-throwing and the self efficacy related to the game were strongly related to interest in the game intrinsically. Self recording increased the skill of the game, beliefs on self reaction and self efficacy.

Similar results in the context of the task of hand writing (Zimmerman and Kitsantas, 1999) with eighty four high school girls as participants, were obtained by the same researchers. They extended their research on the same task on 72 college students (Zimmerman and Kitsantas, 2002) where the impact of modeling and obtaining feedback socially in the acquaition of good hand writing was studied. While one group of students were made to observe a female model student deal and progress gradually in her hand wrinting skill, the other group participants were made to observe a student who was a master in hand writing. But, the later group participants were found to be in a better state when compared to control group participants.

Feedback proved to be highly beneficial to the participants from all the groups in acquisition of self regulatory skills through observation of models.

Schmitz et al., (2011) developed a model of SRL combining the theoretical aspects of both Zimmerman and Kuhl (2006). His research showed that usage of learning diaries improved all the phases of self regulated learning and proved to be an effective intervention in the promotion of SRL and academic performance.

Cattelino et al. (2021) studied the relationship emotional and SRL self efficacy has on positive coping and subjective well-being has on Italian teenagers during the trying times of lockdown during COVID-19 pendamic. Structural equation modeling revealed that positive coping and subjective well-being were predicted by the two forms of self efficacy, disclosing the vital role self efficicacy can play in teenagers to deal with regulation of negative emotions through promotion of appropriate positive coping strategies.

2.3.2Empirical Research Based on Boekaerts' Dual Processing Model of SRL:

Seegers and Boekaerts (1993, 1996) analyzed different dimensions of the cognitive appraisals and how they dictated the expected elating and saddening emotions, intentions of learning and the prospective in general. They found significant differences in the way boys and girls activated different types of appraisals. Boekaerts (1999) found that the intentions of the learning and the manner in which the students gave meaning to specific learning activities were related through variables like self-concept of ability, interest and the activation of goals related to mastery and performance.

The Online Motivation Questionnaire (OMQ) tool based on Dual processing model was used by Boekaerts et al. (1998) and Cronbach et al. (2003) to study the role of thinking and feeling on the intensions of learning and for validated the factor structure of this instrument. The observed data provided support to the existence of seven out of the eight theoretical factors. The seven factors were retained in the study owing to their stable factor structure found to be intact when tested across multiple tasks and time period of six months.

Vermeer et al. (2001) employed the Confidence and Doubt scale instrument, which measures the level of confidence of the subjects on which the instrument is administered for every 40s while they solve mathematics word problems, along with the OMQ, to explore gender difference on this topic. They found that boys enjoyed solving word problems more than girls, displayed more confidence while performing the task, placed more efforts and experienced more positive emotions as well, while girls looked at the task as mere application of some preset rules of the mathematics subject.

Boekaerts et al. (2003) related her dual processing model with the assessment of the outcome of a task using the statistical technique of structural equation modeling. She found that when the students found themselves to competent regarding a task and valued it as well, they experienced positive emotions while performing the task as well. The latter factor was instrumental in placed enhanced efforts during the task.

According to Boekaerts and Cascallar (2006), in this model, the pathway selected by the student can either be well-being centric or mastery centric and hence the name dual processing, while experiencing self regulated learning through a task. These processes are in turn decided by the appraisals made by the student regarding the tasks at hand in him or her, which form the basis for Dual processing model. The set goals are called as “knowledge structures” which determine the manner in which the students would act. If the tasks are assessed to be critical for well-being, strategies to enhance them are activated to save the ego from depletion. Instead, if the tasks are in tandem with the needs, then they beef up the competence and lead to trading of the mastery pathway. Signs of failure in a task can make a learner change his or her track from mastery to wellbeing. The mastery pathway makes up the “top-down” approach as the tasks here are based on the personal goals, values and needs of the learner. The well-being pathway secures the self from destruction forming the “bottom-up” approach. Apart from these purposes of self regulation, the third purpose is experienced by those learners who change their pathway from well-being to mastery, either guided by external forces like mentor/peer pressure or internal forces like thoughts emerging within. A prominent empirical work on this theory was the development of an instrument which measured the emotion regulation strategies developed by the researcher herself (Boekaerts, 2011).

Boekaerts and Rozendaal (2007) employed the Neural Network Methodology, to find whether the poor, moderate and high level performance of hand-writing in students could be predicted through the system of self regulation present in them. The methodology married the biological neural networks with statistics based learning models. It predicted with 94 to 100 percent accuracy the students belonging to three levels of performance based on 56 variables of SRL present in them.

2.3.3Empirical Research Based on Winne and Hadwin's Model of SRL:

Greene and Azevedo (2007) reviewed 113 studies based on this model which support it, covering all the aspects of the model. They explored four possible challenges in the model based on the reviewed empirical evidences. The first challenge was associated with the lack of clarity in the mechanism of working of the phase four. The second was the incorporation of motivation regulation on the basis of the work by Wolters (2003). The third challenge was on the addressal of the evolution of SRL skills over a period of time. The final challenge was pertaining to the study of the effects the characteristics of students have on self regulated learning. Off late, the role of data mining and learning analytics in providing insights on self regulated learning was explored by Winne and Baker (2013).

Summary: Zimmerman's Cyclic model enjoys the fame of being by far the most cited framework behind the empirical research on self regulated learning. The MSLQ tool developed based on this model is one of the mostly validated tools cut across multiple cultures, in spite of its moderate psychometric properties. However the model did not sufficiently touch upon the missing component, emotional regulation strategies, which were taken up by the Dual processing model by Boekaerts and its associated tool, the Online Motivation Questionnaire (OMQ), in its empirical research. A relatively less explored framework of empirical research on self regulated learning is the Winne and Hadwin's model, with its unresolved challenges trying to find inroads through the advancement of data mining and learning analytics.

2.4 Literature Review on Measurement Invariance Testing Research in Self Regulated Learning:

Usher and Pajares (2008) studied the measurement invariance of the Children's self efficacy scale by Bandura with respect to gender and school level, which measured the self efficacy, a vital self regulated learning variable in 3,760 students of 4 to 11 classes. The study found unidimensional factor structure of the construct across elementary, middle and high school students groups. Elementary school students had higher self efficacy when compared to students of middle and high school levels.

Milfront and Fisher (2010) discussed about the importance of equivalence of measures through measurement invariance testing for making comparision of variables across subjects from different groups like gender. The assumption that instruments behave similarly across groups though prevalent is faulty and requires its statistical establishment especially in cross-cultural research. The paper provided an introduction to the concept of measurement invariance and step by step procedure to follow for conducting this statistical technique using the LISREL statistical software.

Klassan (2010) studied the invariance of the 11 items and 7 items version of the Self Efficacy for Self Regulated Learning (SESRL) scale by Bandura (1990), in school and college adolescents with and without learning disabilities. The sample subjects of this study comprised of 146 studenst from the 8^{th} and 9^{th} grades of three high schools in Western Canada. The 7-items shorter version was found to be configural invariant not only for school adolescents, but also for 208 undergraduates students as part of validity check, since the change in CFI index was less than 0.01 (Cheung and Rensvold, 2002) for the shorter version. The reliability coefficients ranged from 0.81 to 0.95, establishing the suitability of the 7-items version of the SESRL scale for administration on both school adolescents and college undergraduates alike.

Alivernini, Lucidi and Manganelli (2011) evaluated the psychometric properties of the Academic Self Regulation Questionnaite (ASRQ) by (Ryan and Cornnell, 1989) by conducting its measurement invariance testing across gender using multi-group confirmatory factor analysis in 1390 Italian elementary school students. The four factor structure of the construct was found to show acceptable goodness of fit with TLI=0.89 IFI=0.91, CFI=0.91 and RMSEA=0.07.The internal consistency Cronbach's alpha varied from 0.6 to 0.88. During measurement invariance testing, the chi-sqaure difference of the baseline model and the scalar model was significant ($p<0.01$) and the Cheung and Rensvold (2002) criterion of ΔCFI <= 0.01, for the acceptance of the invariant null hypothesis, at 0.006, established substantial measurement invariance of the tested scale.

Wang et al., (2013) tested the factorial invariance of self efficacy and self regulated learning along with the english proficiency, between 200 Chinese and 160 German undergraduates. Configural invariance in both the groups for self efficacy and self regulated learning were found using confirmatory factor analysis. The tool used to measure self efficacy, the Questionnaire of English Self-Efficacy (QESE), was found to be factorial invariant in both the groups. However, the SRL tool in English, The Questionnaire of English Self-Regulated Learning Strategies (QESRLS), was found to be variant across groups. The students from both the groups did not differed with respect to SRL strategies employed and English proficiency. But, the Chinese students were found to have lower self efficacy than German students, since there was difference in the factor structure of the construct in both the groups, found through the employment of Structural equation modeling. Reliability estimates tested through internal consistency measure Cronbach's alpha, and test-retest reliability, of the scales were acceptable (Wang, Wang and Li, 2007; Wang et al., 2007).

Honken and Ralston (2013) defined retention rate of as "the percentage of engineering students who continue to pursue a degree in engineering after one year". The retention of first year engineering students is a major issue for engineering institutions across the world. Second year students represent the group of retained students stabilizing the retention rate.

Chasmer et al. (2015) discussed the issue of "Sophomore slump", a term coined by Freedman in 1956. They discussed that sophomore or second year of engineering is crucial year of retention of university students (Brainard and Carlin, 1997), for majors (Min et al., 2011) and has vital impact on the academic success of the students in general (Tobolowsky, 2008). Sophomores were found to experience less connectivity with college in second year due to the lack of specifically designed programs for them, especially in times when they were supposed to be engaged in more academic, professional and social organizations (Sanchez-Leguelinel, 2008). On the contrary, these students were found to be the least involved in studies among the all four levels of graduation, namely, freshmen, sophomores, juniors and seniors (Gardner, 2000). Second year was best suited to include academic programs which would enhance academic success and persistence in learning (Gahagan and Hunter, 2008). Finally, based on Levine and Wyckoff (1990) research where they found that second year is the first step for the students to get introduced to major specific courses, Chasmar et al. (2015) mentioned sophomores to be a natural area of research on ways to enhance retention of students in science and engineering.

Abd-El-Fattah and Salman (2017) applied measurement invariance testing of the Arabic version of academic delay of gratification scale (ADGS) of Bembenutty and Karabenick (2006) on 450 Egyptian adolescents of four public secondary schools. The scale was full measurement invariant with respect to gender. Marsh's (1997) within-network-between network approach was employed to establish construct validity. Under within-network approach, confirmatory factor analysis was conducted to establish the unidimensional nature of the cosntruct. In between-network analysis, the relationship of ADGS was found to be positive with host of theoretical variables like academic achievement, expectancy, utility and linking, and negatively related to social desirability, time and effort for the dimension delay versus non-delay choices in both samples.

Chakraborty (2017c) conducted measurement invariance testing with respect to gender on the academic delay of gratification scale (ADGS) of Bembenutty and Karabenick (2006) with 488 professional courses undergraduate students as the participants, selected using simple random sampling, belonging to the Osmania University, Hyderabad, India. The scale was found to be full metric invariant and partial scalar invariant with respect to gender. The scale showed good fitness measures when confirmatory factor analysis was conducted on it to test its unidimensional factor structure and the reliability measures were also acceptable in the Indian context.

Cadime et al. (2017) studied the measurement invariance with respect of gender and educational level of self regulated learning strategies applied by 1014 students of 1-4 classes and 611 students of 5-6 classes in seven public schools of Portugal, while completing their homework, selected using snowball sampling technique. The instruments used in this study were the Homework Management Scale (Xu, 2008; Yang and Xu, 2015), the Self-Assessment Questionnaire: Homework (SAQ; Hong, Peng, & Rowell, 2009), and The Homework Distraction Scale (HDS; Xu, 2015) for measuring various self regulation related components of homework. The three factors theoretical structure of the tool showed acceptable goodness of fit during confirmatory factor analysis, and there were evidences for partial scalar invariance with respect to gender and elementary and middle school educational qualification levels. The reliability of the three sub-scales was high as well. Girls outperformed boys in all the three factors of homework completion, namely planning, execution and evaluation.

Boer et l. (2018) studied the application of measurement invariance testing in cross-cultural research for ensuring equivalence of the scale tested across subjects of multiple groups based on such recommendations in previous studies (Steenkamp and Baumgartner, 1998; Vandenberg and Lance, 2000; van de Vijver and Leung, 1997). When a research study explores the similarties and differences of the participant subjects from two or more different cultural groups with respect to feelings, thinking or actions, it is called cross-cultural research. They presented a taxonomy of bias, which is error committed systematically during measurement in these studies (van de Vijver and Tanzer, 2004; van de Vijver and Leung, 1997, 2000; van de Vijver and Poortinga, 1997), and where differences in estimates are unexplainable owing to difference in the way the theoretical construct is perceived by the participants (construct bias), or error creeping in to study due to the methodology employed during sampling, tool selection or administration (method bias) or due to item related differences, revealed through differential item functioning (item bias). They reviewed more than 500 published works carried out between 2008 and 2015, only to find that very few studies reported measurement invariance test results among a multitude of such cross-cultural research studies. A hesitation of the research community in the application of this exercise in spite of the availability of statistical techniques and free software like R, was also disclosed in the study, with primary reason for it being lack of awareness on the application of measurement invariance testing before taking up cross-cultural multi-group research. The researchers urged the research community to treat this technique not as an add-on analysis but rather as a necessity in cross-cultural research.

Fischer and Karl (2019) presented an introduction to measurement invariance testing and described three statistical techniques, namely, the exploratory structural equation modeling, iterative hybrid logistic regression and EFA and PCA with Procrustes rotation method in the free software R along with their codes and a sample example.

Martinez (2021) conducted multi group confirmatory factor analysis based measurement invariance testing of the Academic Time Management and Procrastination (ATMPM) measure on first generation and non-first generation college students and found the tool to be configural, metric and scalar invariant.

Summary: Literature review of measurement invariance reveals that a hesitation of the research community in the application of this technique in spite of the availability of statistical techniques and free software like R, is primarily due to lack of awareness of the significance of it before taking up cross-cultural multi-group research. The researchers into the investigation of this technique urge the research community to treat this technique not as an add-on analysis but rather as a necessity in cross-cultural research.

2.5 Literature Review of the Developments in the Estimation of Miscellaneous Estimates, Estimands and Estimators of Psychometrics Auxillary to Measurment Invariance Testing:

The concept of partial measurement invariance testing and its estimators were introduced by Byrne, Shavelson, and Muthen (1989) owing to the strictness of the criterion for measurement invariance in regular situations. Here the constraints are applied only on the factor loadings and item intercepts and items not displaying invariance are removed. However, there are very few benchmarks to follow for removing noninvariant items from the tested scale and re-run it, to establish partial measurement invariance of the instrument across multiple groups.

Vandenberg and Lance (2000) presented the benchmarks for conducting two groups multi-group confirmatory factor analysis study MGCFA. They recommended the Chi/df be less than 3.00, RMSEA be lower than or equal to 0.08, standardized root mean square residual lower than or equal to 0.08, Tucker-Lewis index greater than 0.9, and comparative fit index greater than 0.9, with the ΔCFI less than 0.01 for ensuring invariance of hierarchical models.

Pitt and Myung (2002) remainded that a model is one of the ways of quantitative represention of a theory, the criterion of a model performance through the extent of data reproduction is plagued by the inevitable presence of noise or error in human and animals related research studies. As a result, the accuracy and effectiveness of good of fit estimate takes a double wammy beating. They discussed about the role of Akaike information criterion (AIC) and Bayesian information criterion (BIC) in providing models with justified number of parameters, during model comparison. Complexity was presented as the flexibility possessed by a model to fit in as many number of data patterns within it, by slightly changing a couple of parameters of the study. Generalizability was discussed as the ability of a model to predict beyond a specific sample. Complexity and goodness of fitness are positively related to each other. More the inclusion of parameters in a study, the better would be the agreement of the hypothesized model with the obtained data. But, the graph between generalizability and goodness of fit increases with increase in complexity up to certain point and starts decreasing thereafter.

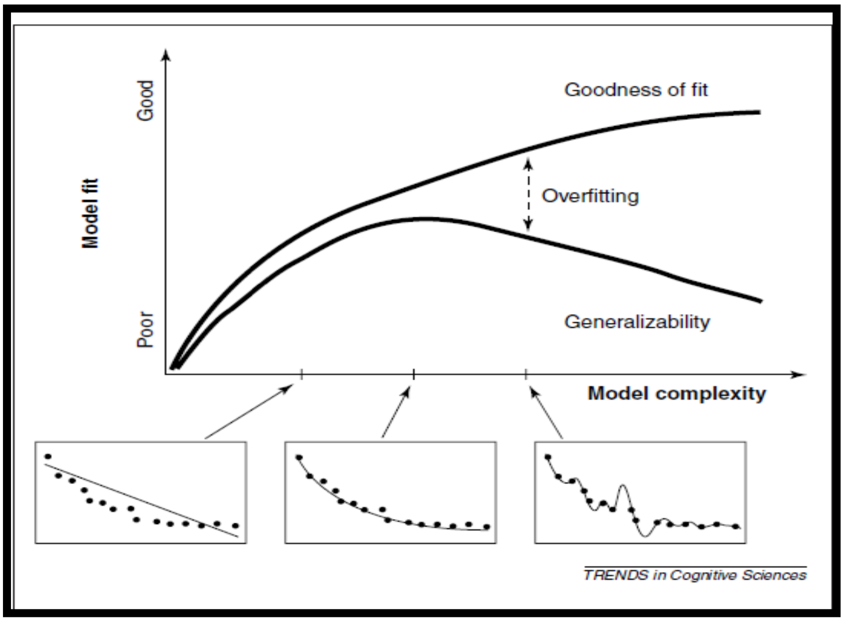


***Figure 2.1*Relationship between Goodness of fit and Generalizability as a Function of Model Complexity, Pitt and Myung (2002)**

The reason for this deviation, they argued, is that beyond the optimal point of generalizability, the realm of overfitting of models begins, where the model engulfs not only the main trend of study but also the small variations introduced due to random errors, negatively impacting the generalizability of the model.

Byrne et al. (2004) mentioned in their study that cross-cultural researchers assume measurement equivalence of a tool when it is proven to be metric invariant across subjects of different cultures. They validated the achievement motivation inventory (Schuler and Prochaska, 2001) on subjects belonging to three different cultures of Germany (n=1433), the US (745) and Israel (n=688). The factor structure and the magnitude of factor loading was found to be same across the participants of this study implying the measurement equivalence of this tool, which in turn allowed the comparison of estimates across groups.

Preacher (2006) explained about the average ability of a model to fit diverse data pattern, when rest of the aspects are held constant, under the concept of fitting parameter (FP) and the role of parsimonious models in this regard. He addressed the critical role of fit and parsimony of a model under the ambit of structural equation modeling. In this context, he drew the attention that instead of comparing the estimates of hypothesized models against arbitrary benchmarks through hypothesis testing, science of psychometrics should instead focus on model selection, where two models compete for their survival based on the extent to which they fit real data. Multiple such performances by a better model can establish its fair representation of the underlying theory (Lakatos, 1970; Meehl, 1990). Also, no model can ever claim to represent its underpinning theory in all possible aspects, and it would suffice if the model shows signs of higher generalizability (McCallum, 2003). While the norm of comparing models against arbitrary benchmarks, leads to confirmation bias latter, making theory-implied models compete which each other can be a far better and scientific approach in congruency with philosophy of science with greater inferences (Platt, 1964).

Hooper, Coughlan and Mullen (2008) mentioned that guidelines for the selection of the fit indices during reporting of the model fit results, should not be based on their prevalence and should be based on variety of these estimands owing to their coverage of different aspects of model fit. Some of the recommended estimands of structural equation modeling which represented the mentioned criteria of variety during the reporting of SEM based model fit results are CMIN/DF, p-value, TLI, CFI, GFI, SRMR and RMSEA.

Dewes (2008) conducted a study to find whether the characteristics of data change when a questionaires' response categories are increased from five, to seven to ten points in a Likert scale. Three groups of participants, with 300, 250 and 185 subjects, were asked to fill a questionnaire of eight items with varying likert scale responses of five, seven and ten categories. The study found that the mean of the measured variable is slightly but significantly less than the mean obtained from five and seven point Likert scales. Other descriptive statistics estimates like standard deviation and skewness did not display any significant difference. It implies that the gradation of the five point scale instruments can be increased to seven point Likert scale without causing any change in the comparison of data in past using the same instrument.

Hamza and Hassan (2009) mentioned the six criteria using which a parsimonious model of an original scale can be obtained in their study. These six criteria are item-total correlation of 0.2 and above, factors with higher eigen values, item-factor laoding of 0.5 and above in constract to the 0.4 benchmark (Heggestad and Kanfer, 1999; Stevens, 1996), items load with higher strength on first factor followed by subsequent factors, factor interpretability and difference in the factor loading of two subsequent factor being at least 0.2.

Davidov et al. (2012) discussed in their work, the options to explore when a study is not find to be measurement invariant across cultures. They recommended that the study can be further carried out by removing the items responsible for non-invariance, the sources of item bias can be identified through the demographic predictors of gender and age, the groups or countries responsible for initial non-invariance be moved, and by stating that partial measurement invariance can be achieved through the presence of at least two invariant items per construct in the tested model.

Wolf et al. (2013) addressed the challenging issue of power analysis or sample size determination in structural equation modeling, by exploring its relation with power, bias and solution propriety. Power is the probability of rejecting null hypothesis when it is false, represented by 1 - β (Cohen, 1988). Bias represents conditions when an estimated parameter is unlike its true population value (Kelley and Maxwell, 2003; Maxwell, Kelley, and Rausch, 2008). Solution propriety reveals whether there are enough cases for the tested model to converge and reveal its estimates (Gagne and Hancock, 2006). Monte-carlo data simulation techniques were employed to draw insights on the research topic. It was found that when there are studies with more sample sizes (Boomsma, 1982; Gagné and Hancock, 2006; Velicer and Fava, 1998), more items per factor to measure it (Gagné and Hancock, 2006; Marsh, Hau, Balla, and Grayson, 1998) and stronger factor loadings (Gagneé and Hancock, 2006), the probability of model to converge or its solution propriety is high. According to Wolf et al., (2013), the criteria for sample size requirement in structural equation modeling, involving CFA, is based upon:

1. **Bias** – Level of significance be 0.05
2. **Power** – 0.8 or more
3. **Solution propriety (model convergence)** – Larger the sample size, lower the errors
4. **Effect of number of factors** – When a latent variable has three or more factors, the effect of sample size is plateaued.
5. **Effect of number of indicators** – Models with fewer indicators requires larger sample size, but the effect is plateaued when the indicators are six or more per latent variable.
6. **Effect of magnitude of factor loading** – Models with stronger factor loadings (above 0.5) requires smaller sample size for model convergence.
7. **Effect of magnitude of factor correlations**- More the interrelationship between the factors, smaller the sample size, keeping the factor loading constant. Rise in factor loadings indicate lesser factor correlation and larger sample size.

Peters (2014) presented the badly flawed nature of underestimation of true reliability of a scale (Raykov, 1997a; Graham, 2006) by the notorious Cronbach's alpha (Sijtsma,2009) in his study, when the conditions of tau-equivalence (Cronbach, 1951) and normality (Green and Yang, 2009a) are violated anywhere between 0.6 to 11 percent depending on how seriously these conditions are violated (Green and Yang, 2009b).

The condition of tau-equivalence expects that the construct is unidimensional and the items measuring it are equally good at measuring it with equal factor loadings. This is most often not the case, as items vary in their ability to measure the latent variable leading to the violation of tau-equivalence condition (Teo,2013; Komaroff, 1997; Zimmerman et al., 1993; Graham, 2006, Peters, 2014).

The violation of the assumptions of tau-equivalence is rampant in the research studies cut across the landscape of social sciences (Osburn, 2000; Gelin, Beasley and Zumbo, 2003; Maydeu-Olivares, Coffman and Hartmann, 2007). Peters (2014) suggested the reporting of alternative estimates of reliability, namely the Greatest lower bound reliability (Woodhouse and Jackson, 1977) and McDonald's omega (McDonald, 2013).

McDonald's Omega addresses the violation of tau-equivalence condition (Dunn and Baguley, 2014) and is immune to the issues arising from the unidimensionlaity or multidimensionality of a construct, a concept known as Congeneric measurement. The effectiveness of McDonald's Omega against the limitations of Cronbach's alpha are well documented in the literature (Revelle and Zinbarg, 2009; Zinbarg, Revelle, Yovel and Li, 2005). However, McDonald's omega performs poorly in the estimation of reliability when the data is non-normal which is more often then not the case (Trizano-Hermosilla and Alvarado, 2016). Raykov's composite reliability is also worth mentioning here as it is an estimator of congenric reliability and free from the under estimation made by Cronbach's alpha in measuring the true reliability of a scale (Raykov, 1997b).

Another less known alternative of reliability estimation suggested by Peters (2014) is the Greatest lower bound reliability (GLB). This estimate is immune to non-normality of the data, violation of the assumptions of tau-equivalence and the issues arising from congenricity of the construct under study, and hence produces better results over alpha and omega (Wilcox et al., 2014). It provides a confidence interval within which the true reliability of the scale lies. However, the only issue with GLB is that it requires large sample size above 1000, which is generally not the case in most of the cross-sectional research. For sample sizes, lower than 1000, GLB has a tendency to inflate the true reliability of the scale (Ten Berge and Socan, 2004).

The data obtained from the responses of subjects from different psychological likert scales are ordinal and Likert scale based like 1=Strongly disagree, 2=Disagree, 3=Neutral, 4=Agree and 5=Strongly Disagree. This calls for the correlation matrix to be converted to polychoric correlation matrix instead of the pearson correlation matrix in order to obtain a true estimate of the reliability (Gadermann et al., 2012). Polychoric correlation provides the measure of relationship through correlation coefficients between variables which are continuous in nature but are measured using ordinal responses of Likert scales. Such correlation matrices are then useful in the estimation of the ordinal versions of alpha (Zumbo, Gadermann, and Zeisser, 2007) and omega (Zinbarg et al. (2005) which are appropriate estimates of reliability using Likert scale based psychological tools. In present study, the latest alternatives of polychoric omega and alpha was reported for the study variables along with their Cronbach's alpha to showcase the disparity in the estimation of the true reliability of the scale by the latter estimatand.

Cho and Kim (2015) dispelled six myths regarding the most widely reported estimate of internal consistency reliability, the Cronbach's alpha, whose properties are not well understood by applied researchers (Green and Yang, 2009). These myths are that alpha is the best estimate among all the other estimates of reliability coefficients, that it was first developed by Cronbach (developed by Guttman), it equals reliability, its estimate can be improved always by deleting items, its high value is an indication of internal consistency and its value must be above or equal to 0.7. They also mentioned that persistence with reporting of alpha is owing to its wide spread popularity and lack of awareness on its shortcomings and on the means to estimate and report better alternatives of reliability.

Golino and Demetriou (2017) presented the powerful technique of Exploratory graph analysis EGA developed by Golino and Epskamp (2016) to determine the number of factors associated with a construct better than the prevailing techniques of Hong Parallel analysis (Hong 1965) andValicer's minimum average partial procedure MAP (Valicer et al., 2000), meant for tools where the items per factor are low and inter-factor correlation above 0.7. EGA has its roots in Network Psychometrics where non-directional network models are measured based on the obtained sample data (Lauritzen, 1996 a, b). These models are made up of "nodes" which are the items of a tool and "edges" which are the statistical connections and among these nodes (Epskamp and Fried, 2016), together forming what is called the pair-wise Markov random field (PMRF, van Borkulo et al., 2014, Costantini et al, 2015a). Whereever the edges are strong among the nodes, potential factors called "clusters" are formed. The formation of the clusters are based on two principles, which are clusters with no connection represent orthogonality between them and the existence of a weighted cluster with every extracted cluster, formed out of the variance-covariance matrix.

This matrix has the partial-correlation coefficients between a pair of nodes in the network model as its elements. The spurious partial correlation coefficients which emerge due to sampling variations are reduced to zero by a powerful regularization technique called the least absolute shrinkage and selection operator (LASSO; Tibshirani, 1996, Epskamp and Fried, 2016, van Borkulo et al., 2014; Kossakowski et al., 2015; Fried et al., 2015), conducted using EBIC technique and a walktrap algorithm (Pons and Latapy, 2005), without causing split loading of items, which is EGA's hall mark over the exploratory factor analysis technique EFA. This leads to conditional independence between nodes, and interpretation of the network model, through fewer edges representing the covariance between the nodes. Rules to follow during the repeated runs of EGA are that when only a single item loads on a factor, it must be deleted, along with deletion of two items of a factor when they cross load on another factor. EGA is followed by confirmatory factor analysis CFA to statistically establish the explored network model.

According to Epskamp et al. (2018), the confirmatory factor analysis under network analysis produces the weighted network, which is regression coefficients mentioned on each of the edge in the network. The significance of these weighted networks are measured using the most central nodes of the graph theory by Newman (2010). Underpinned by the centrality concept (Borgatti, 2015; Costantini et al., 2017; Freeman, 1978), there are three types of this concept called the centrality indices (Costantini et al., 2015a; Newman, 2010; Opsahl et al.,2010), which are technically known as the strength, the closeness and the betweenness. The strength centrality index is the most powerful centrality index (Epskamp et al, 2017), representing the magnitude of the relationship directly shared by a pair of nodes (Barrat et al., 2004). The closeness index of centrality measures the shortest paths through which one node is connected to its nearby nodes, and is effected by any modification in the network model (Borgatti, 2005), caused by the due to the walktrap algorithm. Betweenness centrality index represents the lying of a node in between the edge connecting two other nodes. Direct connections between the nodes representing redundancy is measured through clustering coefficient (Saramaki, Kivela, Onnela, Kaski and Kertesz, 2007; Watts and Strogatz, 1998), which proves handy during the determination of the magnitude and sign of a weighted edge (Saramaki et al., 2007; Costantini and Perugini, 2014). In this way, the weight edges of partial correlation coefficients, represent the strength of the connections between the nodes, representing multivariate normal data in a Pairwise Markov random field, PMRF network model, through the Gaussian graphical model (GGM; Constantini et al., 2015a, Lauritzen, 1996). It uses the correlation matrix proved to it and administers polchoric correlation for ordinal data (Epskamp, 2016) to generate the weighted edges of the nodes. The accuracy of these generated edge weights is dependent of the sample size and there is a scarcity of studies which explored the relationship between edge-weight accuracy and power analysis (Fried, 2016).

Epskamp et al. (2018) developed the mechanism to address the issue indicated by Fried (2016). Since most of the studies in psychology are carried out using moderate sample size, the mechanism makes use of bootstrap technique (Efron, 1979) implemented using LASSO (Hastie et al., 2015), to compensate for the shortage of data due to lower sample size and estimates a “confidence interval (CI)” within which the true edge weights of the nodes exists with 95 percent confidence. The stability of the three centrality indices is measured through “correlation coefficients” of their order in the original network and in a fresh network with lesser number of cases generated through bootstrapping (Chernick, 2011), followed by testing the difference in these two measures again using bootstrapping technique.

According to Epskamp, Borsboom and Fried (2018), network analysis must make use of the theory driven non-parametric bootstrapping, instead of the data driven parametric bootstrapping. Use of parametric bootstrapping causes GGM to treat data as continous instead of its true nature of being categorical ordinal obtained from Likert scale based instruments and does the estimations using Pearson’s correlation instead of the polychoric correlation. Also, LASSO produces biased estimation under parametric bootstrapping over its non-parametric counterpart.

As a part of checking the accuracy of edge weights, the null hypothesis during their significance testing is that they donot differ significantly in strength. Presence of zero in the estimated confidence interval, with negative abscissa and positive ordinate, establishes no such significant difference and hence the acceptance of null hypothesis. CS-coefficient of 0.7 and above between original network data order of centrality indices and its fresh network data, proves large effect size (Cohen, 1977). For practical purposes, it is considered above 0.5 and its value less than 0.25 representing weak result. The final significance test in drawing inference under network analysis, is estimation of difference in the centrality indices and edge weights through a confidence interval, with the presence of zero in the confidence interval establishing the null hypothesis of no significance difference.

Havey (2018) presented an overview of the network analysis concepts and the codes in R to conduct this technique whose roots he cited belonged to the works of van der Maas et al., (2006). Generally the high correlation between a handful of variables indicates the presence of a latent factor bringing the variance in the manifest variables. But, it was van der Maas and his colleagues who proposed that this empirical relationship can also be presented in the form of a network approach, through mutualism model, where variables are mutually related to through varying strength of interconnections among them, thus representing a psychological phenomenon (De Schryver et al., 2015). Here, there is no need of hypothizing the presence of any latent factor and the mutually related variables themselves form a system (Schmittmann et al., 2013).

Olivera-Aguilar and Rikoon (2017) discussed about latent profile analysis as the person-centered method of classifying the group of participants into homogeneous groups called profiles, using continuous manifest variables of distributions of their own. This results in categorical profile groups initially unknown. The profiles are estimated using the data by assigning certain probability to each of the observations and comparing the data with specified models which reveal separation between the profiles (distinctness between the profiles) and homogeneity between the responses in each profile (Collins and Lanza, 2010; Vermunt and Magidson, 2002).

Araujo et al., (2019) applied the person-centred latent profile analysis technique on 2,478 first year Portugese students based on the seven dimensions of academic expectations variable. They extracted six profiles of students, 84 percent of whom displayed average expectations, 8 percent showed very high expectations and four percent showed low expectations. One group of 4 percent presence displayed high expectations on the education quality, political engagement and low expectations in social interactions and giving to pressures from society. Gender-wise, older men showed more positive expectations than their female counterparts.

Christensen et al. (2019) reported the concept of structural consistency for conducting reliability analysis in Network psychometrics, which is a marriage of homogeneity and internal consistency between items (McNeish, 2018). The interconnectivity between nodes in the network remove the aspect of common variance shared under internal consistency (Forbes et al., 2017, 2019), and it becomes necessary to check for the unidimensionality of the nodes in a cluster not just locally but also in the entire network. The intactness measurement of the structure of the cluster nodes in the entire network is done through boot strapping estimator which generates multiple samples from the provided data. Then the estimate of structural consistency estimatand is estimated between 0 to 1. For an instrument with 10 items, an estimate of 0.7, implies that 7 out of the 10 items remain in intact when their structure is searched for intactness in multiple samples, with the rest of three items possessing a tendency to fall apart thorugh split loading.

Chakraborty and Chechi (2020b) applied the techniques of newly evolving area of Network Psychometrics developed by Golino and Demetriou (2017) on the instrument academic emotion regulation questionnaire AERQ developed by Buric et al (2016) by furthering their previous research on the validation of the original (Chakraborty and Chechi,2020a) and its revised versions (Chakraborty and Chechi, 2019). The rationale for application of this new area of dimension extraction through graphical analysis, its theory and all the steps involved in conducting factor analysis through it are mentioned in this work along with their R codes. It also introduces the concept of structural consistency reliability and reporting of its estimates. This study can act as a tutotial for the application of network psychometrics techniques on education related topics in the Indian context.

Summary: Literature review of the developments in the estimation of miscellaneous estimates, estimands and estimators of psychometrics auxillary to measurment invariance testing reveals that the strictness associated with obtaining the complete results of the technique was taken into consideration way back in 1989 when the concept of partial measurement invariance was introduced. Vandenberg and Lance (2000) contributed by presenting the benchmarks for conducting two groups multi-group confirmatory factor analysis study MGCFA. Pitt and Myung (2002) research provided the very important finding that beyond the optimal point of generalizability, the realm of overfitting of models begins, where the model engulfs not only the main trend of study but also the small variations introduced due to random errors, negatively impacting the generalizability of the model. Byrne et al., (2004) provided the finding that achievement of metric invariance in cross-cultural research is assumed to be measurement equivalence of a tool by the research community. Preacher (2006) addressed the critical role of fit and parsimony of a model under the ambit of structural equation modeling, by urging to focus towards selection of models that fit the data well among the competing models, instead of comparing the estimates of hypothesized models against arbitrary benchmarks through hypothesis testing. Since no model can represent the underpinning theory to entirety, it would suffice if the model shows signs of higher generalizability (McCallum, 2003). This will reduce confirmation bias and making theory-implied models compete which each other can be a far better and scientific approach in congreuency with philosophy of science with greater inferences (Platt, 1964). Hooper, Coughlan and Mullen (2008) recommended estimands of structural equation modeling as CMIN/DF, p-value, TLI, CFI, GFI, SRMR and RMSEA. Hamza and Hassan (2009) mentioned the six criteria using which a parsimonious model of an original scale can be obtained in their study. Davidov et al. (2012) discussed in their work, the options to explore when a study is not find to be measurement invariant across cultures. Wolf et al. (2013) addressed the challenging issue of power analysis or sample size determination in structural equation modeling, by exploring its relation with power, bias and solution propriety. On the front of reliability estimation, Peters (2014) presented the badly flawed nature of underestimation of true reliability of a scale (Raykov, 1997a; Graham, 2006) by the notorious Cronbach's alpha (Sijtsma,

2009) in his study, when the conditions of tau-equivalence (Cronbach, 1951) and normality (Green and Yang, 2009a) are violated anywhere between 0.6 to 11 percent depending on how seriously these conditions are violated (Green and Yang, 2009b). The data obtained from the responses of subjects from different psychological likert scales are ordinal and Likert scale based like 1=Strongly disagree, 2=Disagree, 3=Neutral, 4=Agree and 5=Strongly Disagree. This calls for the correlation matrix to be converted to polychoric correlation matrix instead of the Pearson correlation matrix in order to obtain a true estimate of the reliability (Gadermann et al., 2012). As a result, the latest alternatives of polychoric omega and alpha must be reported for the study variables along with their Cronbach's alpha to showcase the disparity in the estimation of the true reliability of the scale by the latter estimatand. Golino and Demetriou (2017) presented the powerful technique of Exploratory graph analysis EGA developed by Golino and Epskamp (2016) to determine the number of factors associated with a construct better than the prevailing techniques of Hong Parallel analysis (Hong 1965) and Valicer's minimum average partial procedure MAP (Valicer et al., 2000), meant for tools where the items per factor are low and inter-factor correlation above 0.7. EGA has its roots in Network Psychometrics, which is an emerging state of art field of psychometrics in general. Christensen et al. (2019) reported the concept of structural consistency for conducting reliability analysis in Network psychometrics, which is a marriage of homogeneity and internal consistency between items (McNeish, 2018). Chakraborty and Chechi (2020b) applied the techniques of newly evolving area of Network Psychometrics developed by Golino and Demetriou (2017) on the instrument academic emotion regulation questionnaire AERQ developed by Buric et al (2016), with the intent that this study can act as a tutorial for the application of network psychometrics techniques on education related topics in the Indian context.

2.6 Conceptual Frameworks:

The following conceptual frameworks are proposed for testing, based on the above conducted literature review:

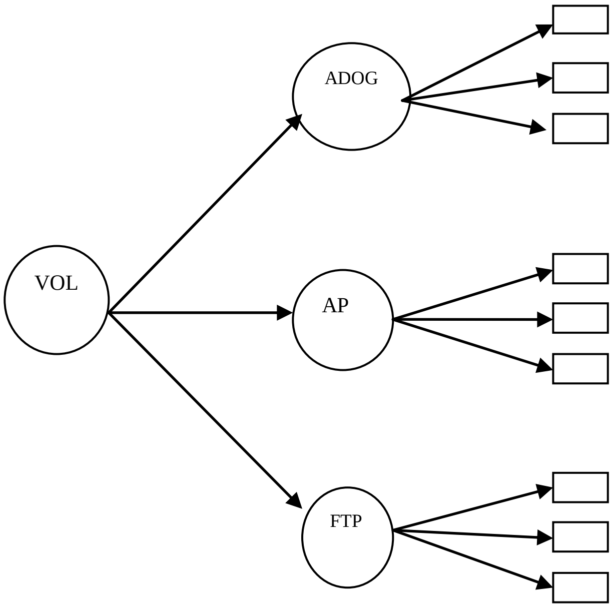


Figure 2.2 **Framework of the Trait Model of Volition for SRL to be Validated in the Indian Context**

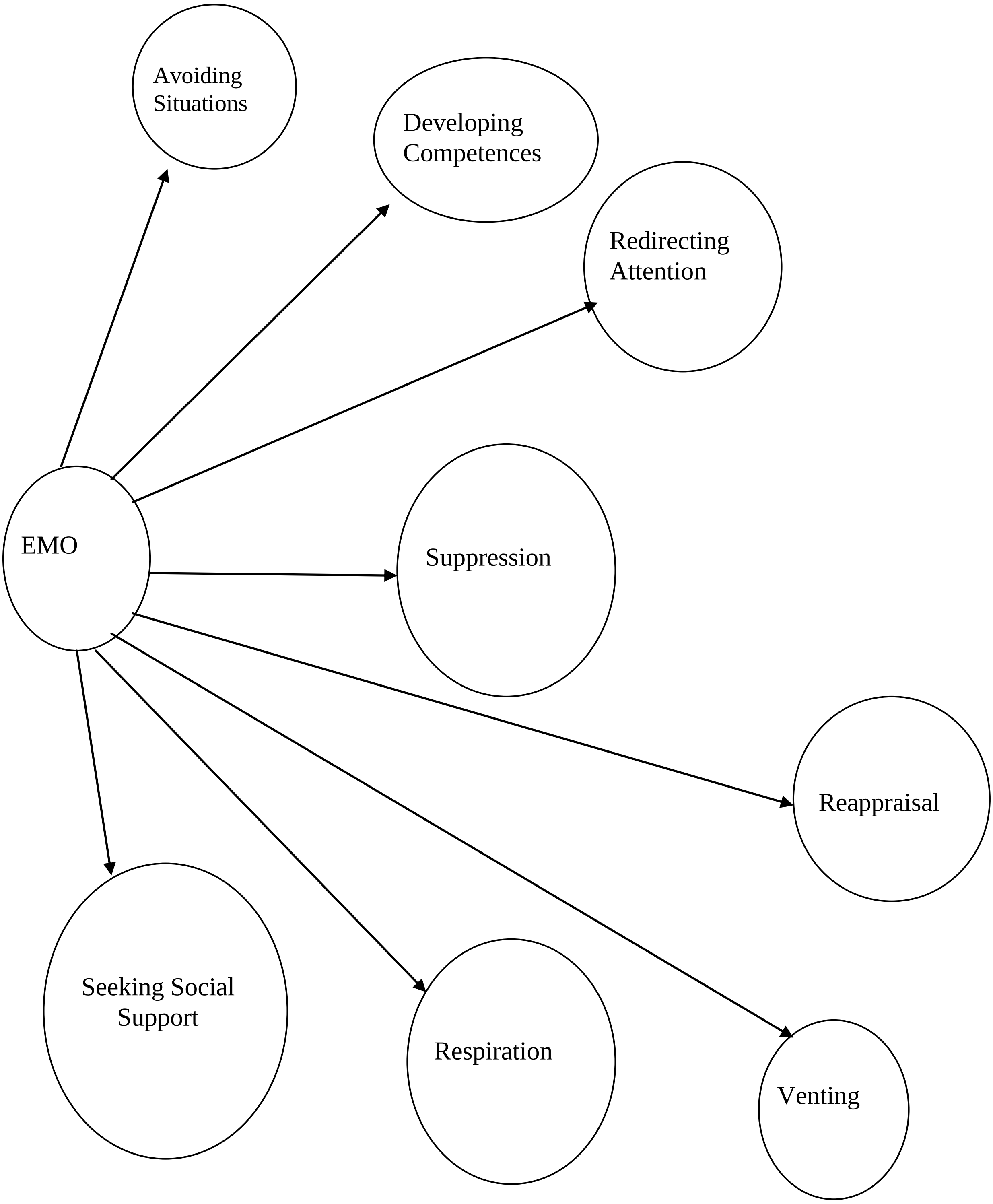


Figure 2.3 **Framework of Trait Model of Emotional SRL Strategies to be validated in the Indian Context**

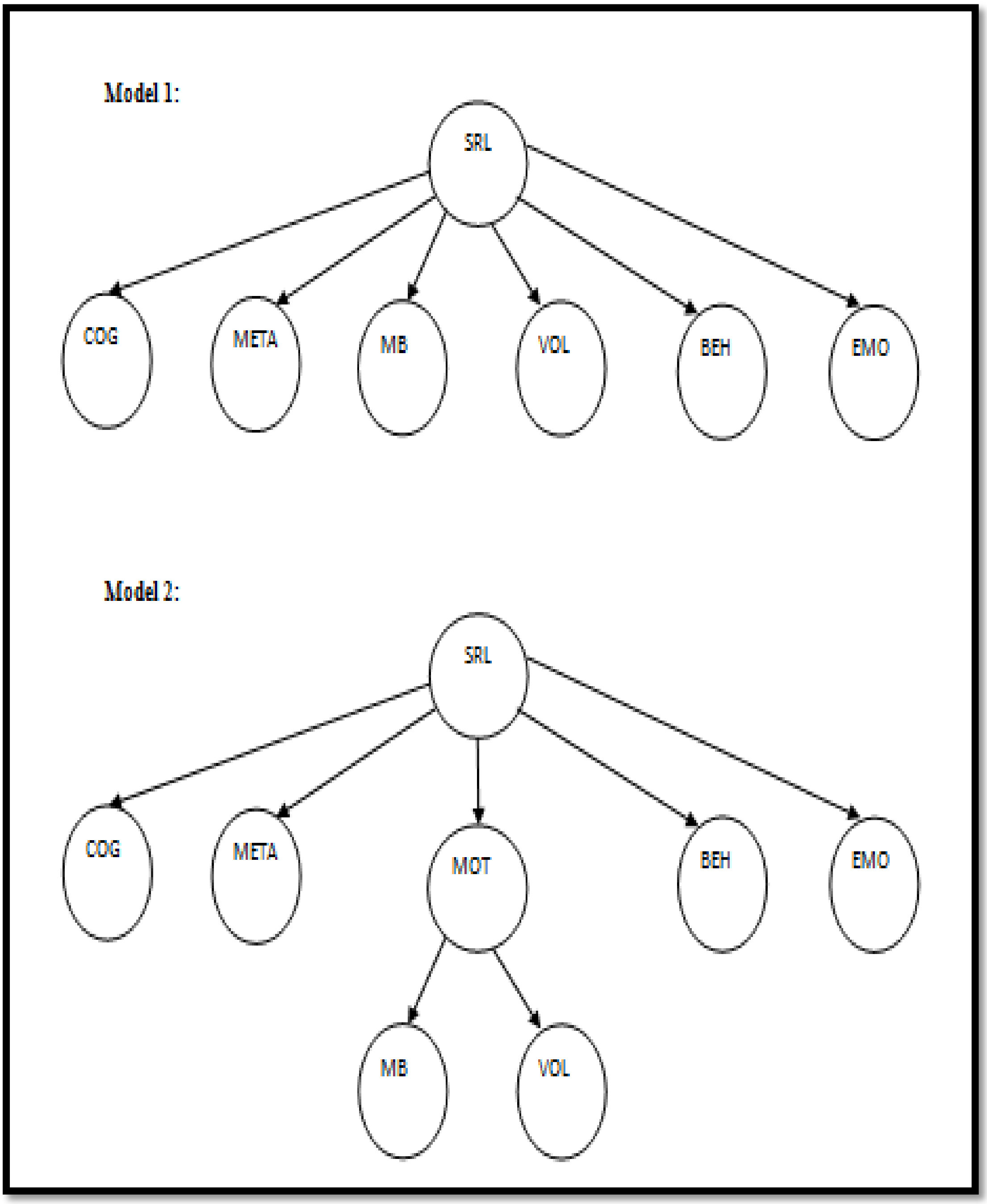


Figure 2.4**Two Integrative SRL Models of Volition's place in the SRL framework**

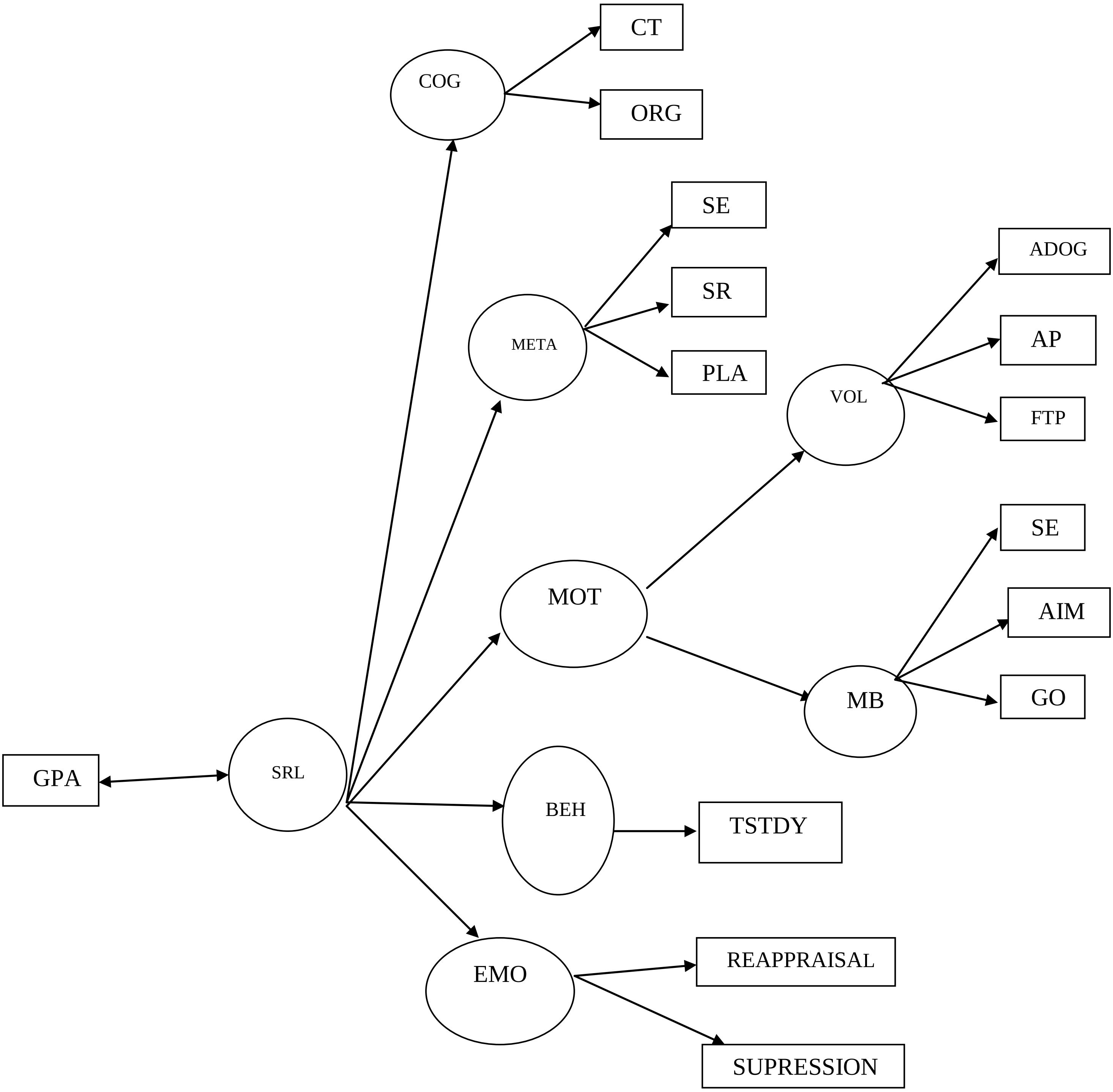


Figure 2.5 **Structural Equation Model of Trait SRL and Academic Achievement**

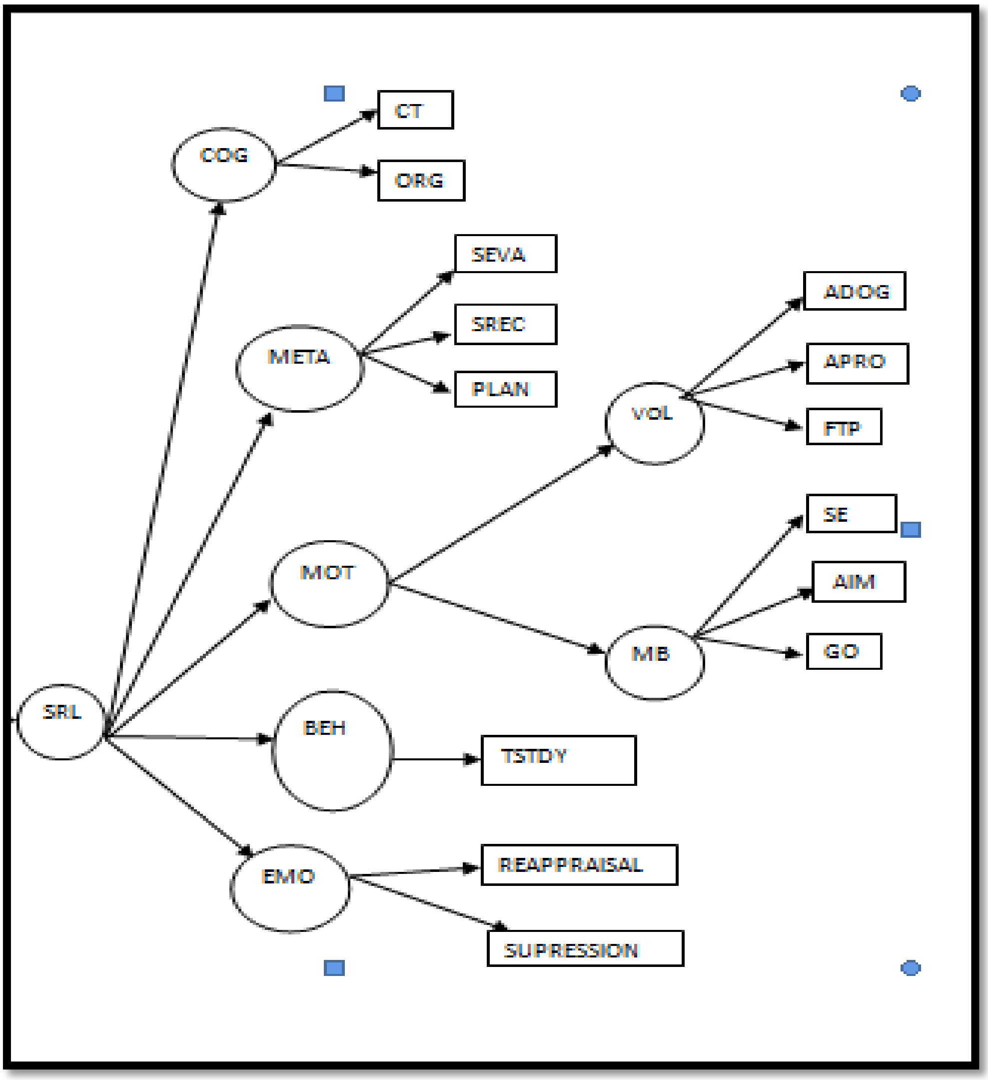


Figure 2.6 **Path Diagram for Configural Measurement Invariance Testing of the Integrative Trait Model of SRL with respect to Gender, Batch and Stream of Engineering Undergraduates.**

Conclusion: The next chapter discusses the design using which the data was collected, for further analysis, interpretation and reporting. The rationale of selection of the population and the sample are also explained in the succeeding chapter, along with the details of the tools using which the data was collected.

CHAPTER 3

RESEARCH DESIGN

3.1 Introduction

After conducting a detailed literature review of the research problem, the next step of advancement involves the planning or designing of the research study (Creswell,2016). The research design is the blueprint of the manner in which the researcher would collect, analyze and interpret the data of the variables in the study. In Social Sciences research, the gathered data pertinent to the research problem, provides the evidence to properly establish the phenomenon under study. The research problem decides the type of the design to adopt (De Vaus, 2001, William, 2006).

There are three types of research design studies. They are namely, the qualitative, quantitative and mixed research studies. According to Morse (1991), the qualitative research problem is taken up with an exploratory perspective, intended to study concepts that are still “immature” and where is a lack of theory to back it, scarcity of research literature for guidance, are the existing theories are either biased or inaccurate or the phenomena under study does not qualify for quantitative analysis. Quantitaive research is taken to determine the factors responsible for the apparent existence of a phenomenon and also for advancing the testing of a theory whose research questions rest on detailed literature review. When ever the topic of interest involves the study of the underlying factors and also their further exploration, the marriage of qualitative and quantative approaches, called the mixed method is employed.

All the theories of the 14 variables under the five components of trait based self regulated learning are available and the research on these variables is backed by sufficient availability of literature. Also, the nature of the research problem of this study is such that it calls for a quantitative research design here. The relationships among variables are best studied under quantitative research through surveys and experiments. Here, a strict research design and application of statistical analysis on parsimonious set of variables leads to their measurement for testing a theory, backed by empirical observed data. Testing the validity and reliability of the tools of measurement and the scores hence obtained by administering them on a targeted audience, provides meaningful interpretation of data.

While the experimental study intends the test the impact of an intervention or treatment on an outcome, by controlling the confounding variables, the survey design helps in the quantitative description of opinions, attitudes and trends prevalent in a society among a certain population. In both the cases, the results obtained from the sample, are generalized over the entire population. Since the present study, intends to measure the presence of trait self regulated learning in its target population in a cross-sectional mode through the administration of a questionnaire and online survey (Nesbary, 2000; Sue and Ritter, 2007), the survey method of data collection is selected in this study (Babbie, 1990; Fink, 2002).

Table 3.1 Components of a Survey Method of Data Collection:

S.No.	Component of Survey Method
1.	Statement of the purpose of the survey design
2.	Mentioning of the reasons for choosing survey design
3.	Identification of the nature of the survey (CrosssectionalVs Longitudinal)
4.	Mentioning of the population along with its sampe size
5.	Procedure of the stratification of the population
6.	Selection criteria of the sample and its size
7.	Procedure of the sampling of the participants (Random Vs Non-random)
8.	Details of the instruments used in the study
9.	The dimensions of the survey instruments
10.	Procedure of pilot study of the survey
11.	The timeline of the survey’s administration
12.	Variables of the study
13.	Cross-references of the study variables with the research questions and items of the survey
14.	Steps to analyze the data
15.	Steps to check bias in the responses of the subjects
16.	Steps of Descriptive analysis
17.	Steps to collapse the items under sub-scales of the each scale
18.	Steps to conduct Reliability analysis of the scales
19.	Steps of Inferential analysis
20.	Steps to interpret results

The succeeding sections of the chapter three provide the rationale for the selection of the population, discuss the sampling design, determine the sample size, list the tools of the study along with their descriptions and present the chronology of the statistical techniques applied on the data and their respective statistical software.

3.2 Rationale for the Selection of the Population:

According to the sixth edition of India Skill Report (2019) which provides the state of art with respect to talent landscape of the country, by 2022, India would have a workforce estimated at nearly 600 million. It will be among the handful of nations in the world which would be able to meet its labour requirements owing to the median age of its workforce being 28 years. In this context, the most employable talent in our nation lies in the domain of B.E./B.Tech. Moreover, it is also the segment from which hiring happened the most in the recent years. During the hiring, even in education domain–wise, the engineers are at upper hand. Electronics and Communication engineering tops the course-wise employability list, with civil engineering being the least employable course off late. Hiring from the campus remains the second most preferred source or channel for recruitment of the workforce. The three most preferred skills of the employers during hiring are the communication skills, the ability to adapt in a new environment and learning agility in the talent of interest.

Owing to the apparent significance of the engineering, as the primer of the labour work force and successively the economy of India, the present study intended to take up the undergraduates pursuing this vital profession as the population of interest.

SKILLS	2014	2015	2016	2017	2018	2019
	YEARS					
B.E/B.Tech	51.74%	54.00%	52.58%	50.69%	51.52%	57.09%
MBA	41.02%	43.99%	44.56%	42.28%	39.4%	36.44%
B.Arts	19.10%	29.82%	27.11%	35.66%	37.39%	29.3%
B.Com	26.99%	26.45%	20.58%	37.98%	33.93%	30.06%
B.Sc	41.66%	38.41%	35.24%	31.76%	33.62%	47.37%
MCA	43.62%	45.00%	39.81%	31.36%	43.85%	43.19%
ITI	46.92%	44.00%	40.90%	42.22%	29.46%	NA
Polytechnic	11.53%	10.14%	15.89%	25.77%	32.67%	18.05%
B.Pharma	54.65%	56.00%	40.62%	42.30%	47.78%	36.29%

Figure 3.1 **Domain-wise Employable Talent – India Skill Report (2019)**

DOMAIN WISE PERCENTAGE	2014	2015	2016	2017	2018	2019
Undergraduate or Equivalent	6	6	8	6	14	12
ITI	6	7	14	13	7	12
Polytechnic	8	4	7	11	4	7
PG Or Equivalent (MCA/MSC/MA/M.com/CA/M.Tech)	6	8	8	6	10	11
Management or Equivalent -MBA, PGDM	22	22	16	16	19	13
Graduates - BCA/BBA/B.Com/BSc.etc	24	23	23	23	24	22
Engineers (BE/B.Tech)	28	29	25	25	22	23

Figure 3.2 **Domain-wise Hiring – India Skill Report (2019)**

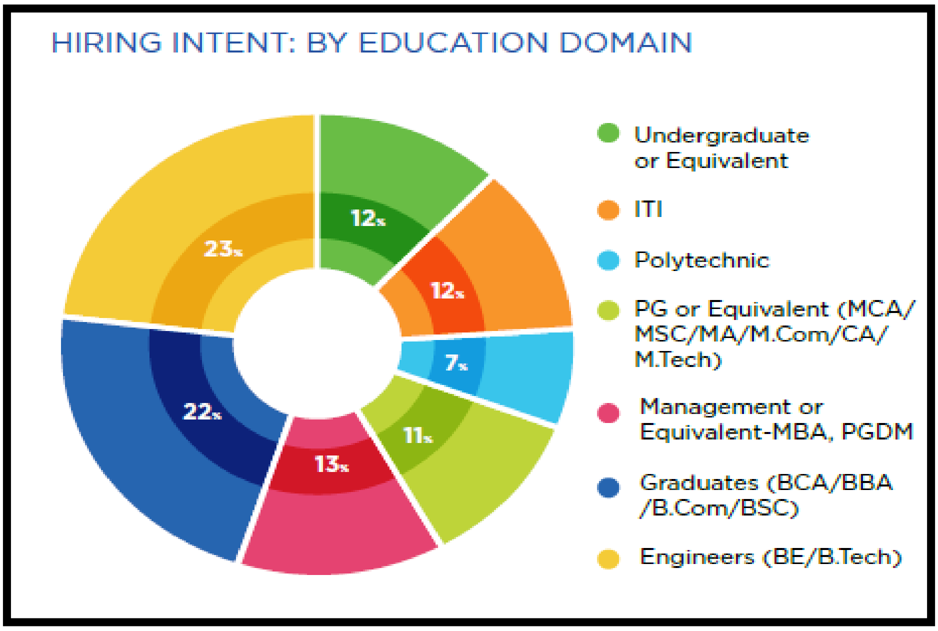


Figure 3.3 **Education Domain-wise Hiring – India Skill Report (2019)**

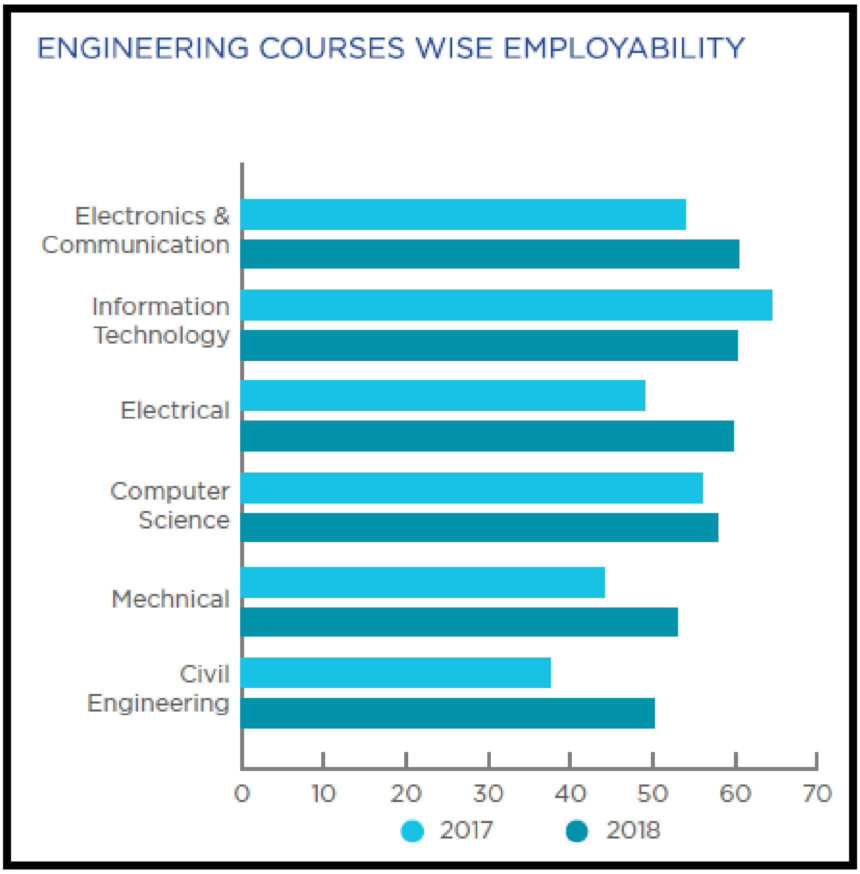


Figure 3.4 **Course-wise Employability – India Skill Report (2019)**

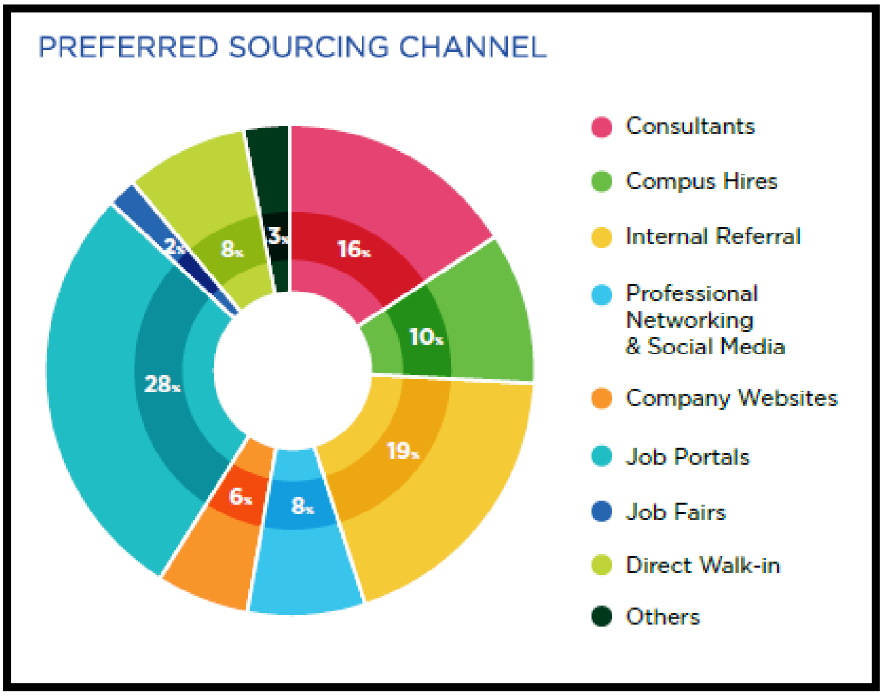


*Figure 3.5***Preferred Hiring Sources or Channel – India Skill Report (2019)**

The academic achievement of the engineering student attending the campus drive, serves as an apparent quantitative indicator of the presence of these preferred skills. Also, learning agility requires an intent of life long learning in the student even after, the student is hired. The link between the academic achievement of a to-be hired engineering student and a life long learning employee is the aspect of self regulated learning. Self regulated learners are autonomous in nature and not only perform well in academics (Alotaibi,Tohmaz and Jabak, 2017), but also continue to upgrade their knowledge, skill and attitude all along their life.

Moreover, on the flip side, the duration of engineering course is of four years. It is a content overloaded program where the faculty do not get enough time to complete the syllabus, leave alone expecting them to extract time and teach the students how to be academically successful by learning self regulation in academics (McCord, 2016). This leads to either drop-outs or graduation of poor quality engineers in large numbers. The need to identify self regulated engineering students and maladjusted self regulated engineering students must be acknowledged by engineering institutions in India if they desire to produce quality engineers. This calls for designing of the engineering course and student training to promote self regulated learning in engineering, which in turn requires the existence of an empirical comprehensive and integrative self regulated learning model, which is what is intended in this study.

In this context, according to Chasmar et al. (2015), the natural area for research to focus for the retention of students in science and engineering is sophomore or the second year, owing to the concept of Sophomore Slump. It is defined as “a loss of students’ engagement as they return and begin their second year” (McBurnie, Campbell and West, 2012). It happens because of the additional academic and social stressors experienced by the second year students when compared to the first years. The first years have to get adjusted into the new role of a university student and sufficiently deal with the new rewards and threats it brings. On the contrary, the second years not only have to be maintain their earlier academic and social engagements in the campus, but also take decision on defining their sense of purpose in life, choosing their major topic of study and narrowing their professional options, all of which have lifelong consequences (Tobolowsky, 2008). Research by Graunke and Woosley (2005) found that the certainity with which students chose their majors, predicted their higher academic performance. These students are more driven when compared to their peers and this drive inturn focuses them and acts as a radar in their integration whole-heartedly to the program they are pursuing. Owing to this reason of the second year being the choice of majors (Levine and Wyckoff, 1990), it because the quintessential area of research on finding the means to retain students in science and engineering (Chasmar at al., 2015). While the first years are paid attention by institutions for their retention, final years are attended for placements. But in spite of the established challenges they face and the critical role of this batch in academic success, the second year students along with third year students or juniors, are the neglected lot and an increased focus on these students is justified (Tobolowsky, 2008).

Though the second year should be a time when students get involved in professional, social and academic organizations, sophomores often feel less connected to campus due to lack of programs specifically designed for them (Sanchez-Leguelinel, 2008). Sophomores are found to be the least academically involved out of the four typical student levels, that is, freshmen, sophomores, juniors and seniors (Gardner, 2000). Ultimately, this leads to fewer students obtaining a postsecondary degree and, even further, a better, more desired position in the workforce and their subsequent careers.

This calls for the need to conduct research to explore the emotional, behavioral and cognitive aspects of self regulation and means of their promotion in sophomore students, as little research is available on it in the backdrop of Sophomore slump. Such studies would help in profiling of sophomore students based on the SRLstrategies employed by them in engineering, which can further lead to development of the much needed intervention programs to curb the issue of disengagement and maintain retention of these students (LeMay, 2017).Hence, the students from second, and the next successive group, third year, represented the universe of subjects in this study.

These students were chosen from the most common branches, namely, Computer Science and Mechanical engineering. It is because according to the All India Survey on Higher Education 2019 report by the Ministry of Human Resource Development, Department of Higher Education, Government of India, the top five branches of engineering were Computer Engineering with 8.8 lakh students, Mechanical Engineering with 7.8 lakh students, Electronics Engineering with 6.31 lakh students, Civil Engineering with 5.36 lakh students and Electrical Engineering with 3.94 lakh students enrolled. While the students from computer and mechanical engineering were 16.8 lakh, the students from the other three streams, electronics, civil and electrical engineering, were 15.61 lakh collectively.

3.3 Sampling Design:

3.3.1 Sampling Frame Determination

The state of Punjab can be broadly divided into three regions, namely, Majha, Malwa and Doaba, comprising of 22 districts, as per the details given below:

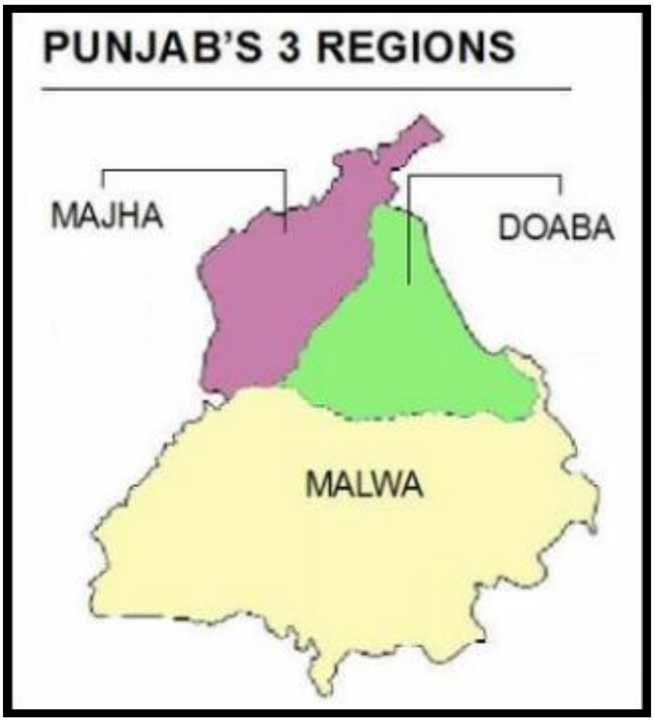


***Figure 3.6*The Three Regions of Punjab**

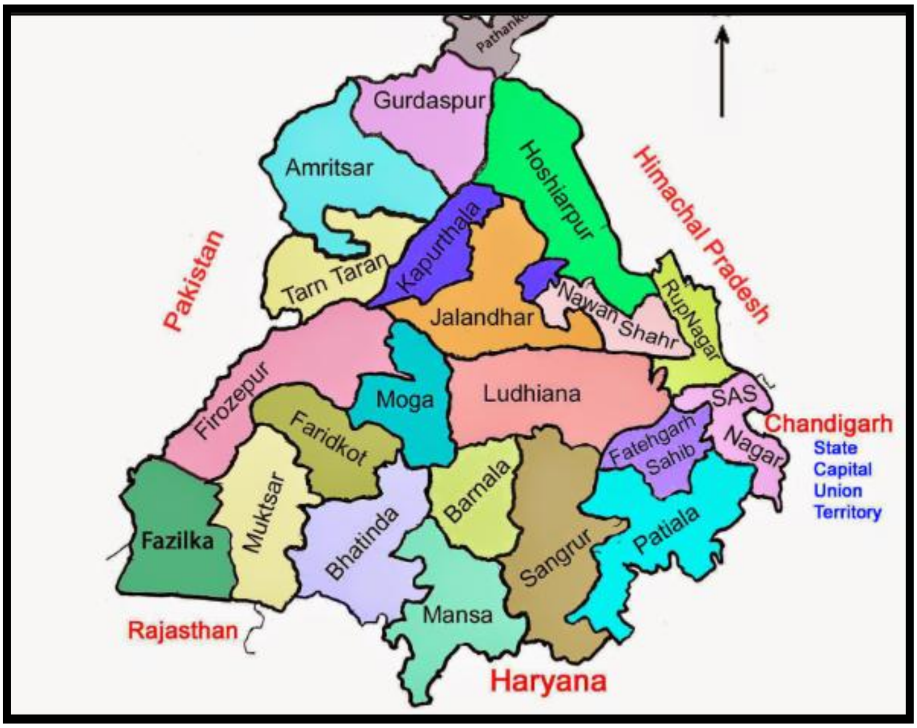


*Figure 3.7***The 22 Districts of Punjab**

S.No.	**Table 3.2 Distribution of 22 Districts of Punjab as per the Three Regions –** Kohar (2016)		
	Region 1 : Majha (04)	**Region 2 : Doaba (05)**	**Region 3 : Malwa (13)**
1.	Pathankot	Hoshairpur	Firozpur
2.	Gurdaspur	Kapurthala	Bathinda
3.	Amritsar	Jalandhar	Ludhiana
4.	Tarn Taran Sahib	Nawanshahr	Moga
5.		Rupnagar	Burnala
6.			Mansa
7.			Faridkot
8.			Fatehgarh Sahib
9.			Sangrur
10.			Sri Muktsar Sahib
11.			Mohali
12.			Fazilka
13.			Patiala

The branches of Computer Science and Engineering and Mechanical Engineering are offered in these 22 districts of Punjab by both U.G.C. recognized universities with AICTE approved courses taught in them and A.I.C.T.E. recognized engineering colleges themselves.

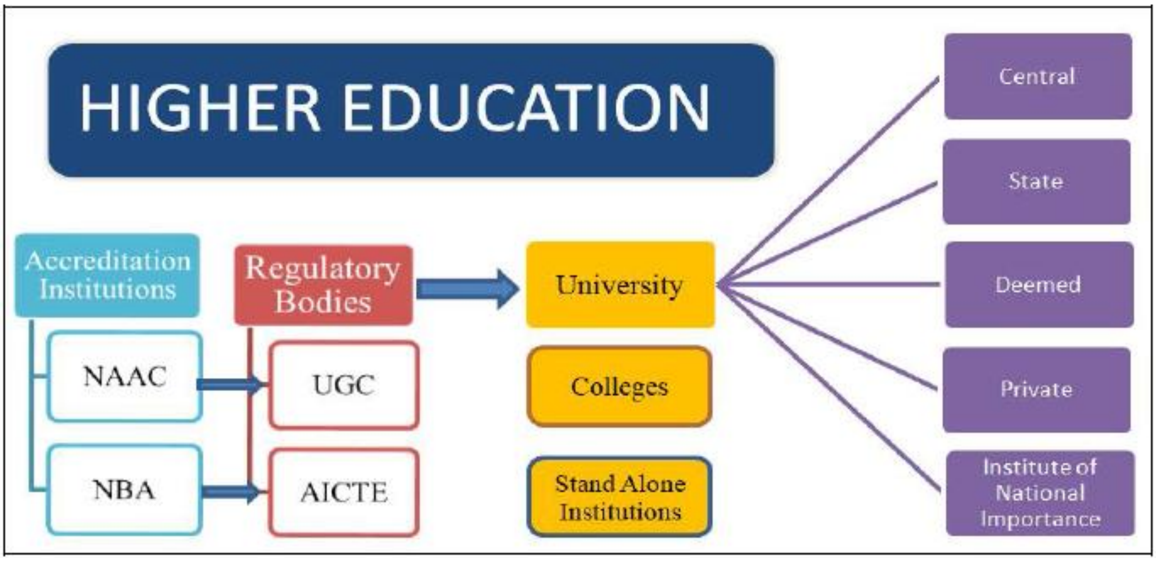


*Figure 3.8***Structure of higher education in India**

The total number of these U.G.C. recognized universities and A.I.C.T.E. approved engineering colleges, in Punjab, comprise the population of this study.

3.3.1.1 Determination of UGC Recognized Universities Offering Computer Science and Mechanical Engineering Branches:

According to the list of recognized Indian universities released by the University Grants Commission, New Delhi on 01.06.2020, there are 28 universities in the state of Punjab, with break-up shown below:

Table 3.3 List of Universities in Punjab

S.No.	Universities in Punjab, India	**Quantity (28)**
1.	Central Universities	1
2.	State Universities	8
3.	Private Universities	15
4.	Deemed Universities	2
5.	State Technical Universities	2

Source:https:// www.ugc.ac.in

17 of these universities offering undergraduate engineering programs, form the sampling frame of U.G.C. approved universities, as the rest belong to other disciplines like Health sciences, Law, Ayurveda, Veterinary etc, and/or are located outside the geographical territory of Punjab and hence excluded from the study, with details shown below:

Table 3.4 Region-wise Details of the Universities of Punjab:

S.No.	Name of the University in Punjab	Region	Type	No. of Institutions	Status in Study	Reason for Exclusion
1.	Central University of Punjab	Malwa	Central	1	Excluded	Offers P.G. Engineering Programs only
2.	Sant Longowal Institute of Engineering and Technology (SLIET)	Malwa	Deemed	2	Excluded	Present in AICTE List of Institutions 2020-21
3.	Thapar Institute of Engineering & Technology	Malwa			Excluded	Present in AICTE List of Institutions 2020-21
4.	Baba Farid University of Health Sciences	Malwa	State / Public	10	Excluded	Does not offer U.G. Engineering Programs
5.	Guru AngadDev Veterinary and Animal Sciences University	Malwa			Excluded	Does not offer U.G. Engineering Programs
6.	Guru Nanak Dev University	Majha			Included	N/A
7.	Guru RavidasAyurdev University	Doaba			Excluded	Does not offer U.G. Engineering Programs
8.	Maharaja Ranjit Singh Punjab Technical University	Malwa			Included	N/A

9.	Punjab Agricultural University	Malwa			Excluded	Does not offer U.G. Engineering Programs
10.	Punjabi University	Malwa			Included	N/A
11.	Panjab University	Doaba			Excluded	Union Territory
12.	The I.K. Gujaral Punjab Technical University	Malwa			Excluded	Present in AICTE List of Institutions 2020-21
13.	The Rajiv Gandhi National University of Law	Malwa			Excluded	Does not offer U.G. Engineering Programs
14.	Adesh University	Malwa	Private	15	Excluded	Does not offer U.G. Engineering Programs
15.	Akal University	Malwa			Excluded	Does not offer U.G. Engineering Programs
16.	Chandigarh University	Doaba			Excluded	Present in AICTE List of Institutions 2020-21
17.	Chitkara University	Malwa			Included	N/A
18.	C.T. University	Malwa			Included	N/A
19.	D.A.V. University	Doaba			Included	N/A
20.	Desh Bhagat University	Malwa			Included	N/A
21.	GNA University	Doaba			Included	N/A
22.	Guru Kashi University	Malwa			Excluded	Present in AICTE List of Institutions 2020-21
23.	Lovely Professional University	Doaba			Included	N/A

24.	RayatBahra University	Doaba			Included	N/A
25.	RIMT University	Malwa			Excluded	Present in AICTE List of Institutions 2020-21
26.	Sant Baba Bhag Singh University	Doaba			Included	N/A
27.	Sri Guru Granth Sahib World University	Doaba			Excluded	Union Territory
28.	Sri Guru Ram Das University of Health Sciences	Malwa			Excluded	Does not offer U.G. Engineering Programs
				28	**11**	

Table 3.5 List of Universities of Punjab Included in the Sampling Frame of the Study:

S.No.	Name of the University Offering Computer Science and Mechanical Engineering - U.G.C.	Region
1.	Guru Nanak Dev University	Majha
2.	Maharaja Ranjit Singh Punjab Technical University	Malwa
3.	Punjabi University	Majha
4.	Chitkara University	Malwa
5.	C.T. University	Malwa
6.	D.A.V. University	Doaba
7.	Desh Bhagat University	Malwa
8.	GNA University	Doaba
9.	Lovely Professional University	Doaba
10.	RayatBahra University	Doaba
11.	Sant Baba Bhag Singh University	Doaba

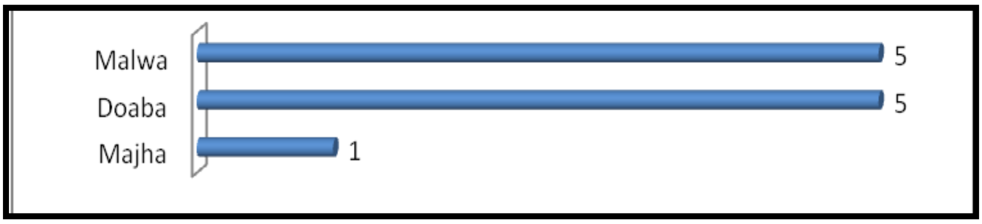


Figure 3.9 **Region-wise Distribution of Universities Offering Computer Science and Mechanical Streams of Engineering in Punjab**

3.3.1.2 Determination of AICTE Recognized Colleges Offering Computer Science and Mechanical Engineering Branches:

The number of AICTE recognized colleges offering Mechanical engineering program for the academic year 2020-2021 in the state of Punjab as per AICTE website displayed 79 institutions:

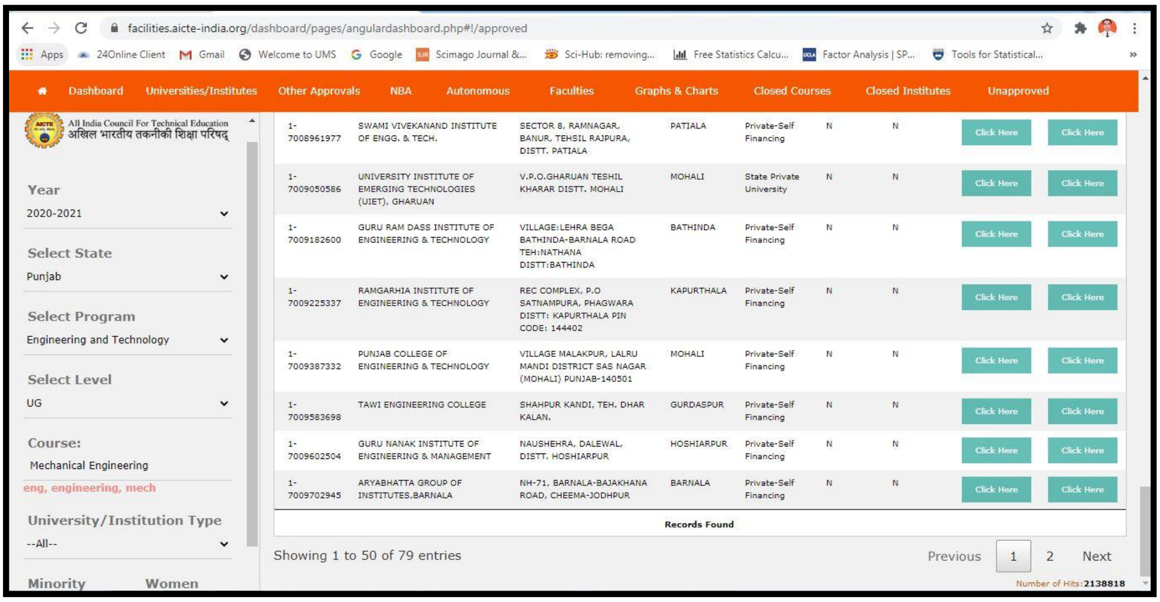


Figure 3.10 **Number of Mechanical Engineering Institutions in Punjab as per AICTE in the Academic Year 2020-21**

The number of AICTE recognized colleges offering Computer Science engineering program for the academic year 2020-2021 in the state of Punjab as per AICTE website displayed 46 institutions:

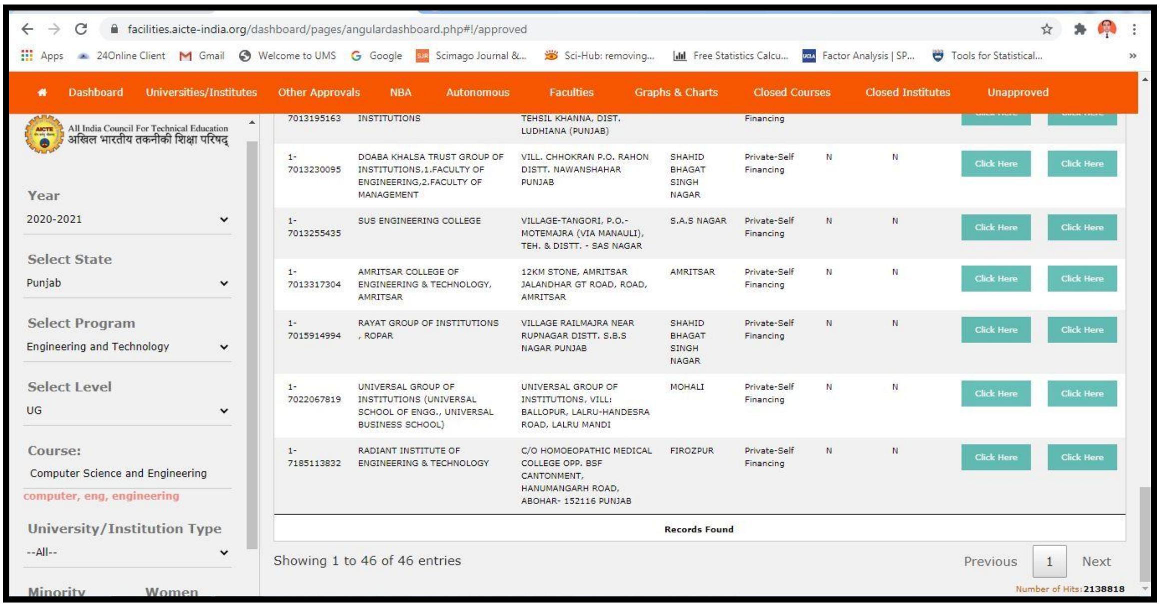


Figure 3.11 **Number of Computer Science Engineering Institutions in Punjab as per AICTE in the Academic Year 2020-21**

This called for the consolidated 125 instituitions list be searched for redundancy of names of institutions for the sake of determination of the sampling frame of the A.I.C.T.E. approved institutions. 42 such institutions were revealed, which were removed from the list, bringing down the consolidated list of AICTE recognized institutions offering both Computer Science and Mechanical branches of engineering in Punjab to 83, out of which 17 of these institutions were located in Majha region, 17 of them belong to Doaba region and 49 of them were situated in Malwa region, completing the sampling frame determination, whose details as per their respective region are given below:

Table 3.6 List of AICTE Recognized Engineering Institutions in Majha Region as per AICTE (2020-2021):

S.No.	Aicte ID	Name	District	Region
1	1-7003159712	Sai Institute of Engineering & Technology	Amritsar	Majha
2	1-7003199822	Global Group Of Institutes	Amritsar	Majha
3	1-7003409486	Shiv Shankar Institute Of Engineering And Technology	Taran Taran	Majha
4	1-7004861580	Radical Technical Institute	Amritsar	Majha
5	1-7004949055	Baba Kuma Singh Ji Engg College	Amritsar	Majha
6	1-7008764885	Swami Sarvanand Institute of Engineering & Technology	Gurdaspur	Majha
7	1-7009811146	Beant College of Engineering & Technology,Gurdaspur	Gurdaspur	Majha
8	1-7013161156	Khalsa College of Engineering & Technology	Amritsar	Majha
9	1-7013175923	Sukhjinder Technical Campus	Gurdaspur	Majha
10	1-7013317304	Amritsar College Of Engineering & Technology	Amritsar	Majha
11	1-7001875358	Aman Bhalla Institute of Engineering and Technology	Gurdaspur	Majha
12	1-7002909003	S.Sukhjinder Singh Engineering & Technology College	Gurdaspur	Majha
13	1-7005072724	Satyam Institute Of Engineering & Technology	Amritsar	Majha
14	1-7009583698	Tawi Engineering College	Gurdaspur	Majha
15	1-7012909478	Golden College of Engineering & Technology	Gurdaspur	Majha

16	1-7012990033	M K Education Societie's Group of Institutions	Amritsar	Majha
17	1-7015891644	Sri Sai College of Engg. & Tech	Gurdaspur	Majha

Table 3.7 List of AICTE Recognized Engineering Institutions in Doaba Region as per AICTE (2020-2021):

S.No.	Aicte ID	Name	District	Region
1	1-7002505328	Institute of Engineering & Technology	Rupnagar	Doaba
2	1-7003476133	Ct Institute Of Technology	Jalandhar	Doaba
3	1-7003728443	Rayat Bahra Institute of Engineering and Nano-Technology	Hoshiarpur	Doaba
4	1-7003830422	Global College of Engineering and Technology	Rupnagar	Doaba
5	1-7006832870	Anand College of Engineering & Management	Kapurthala	Doaba
6	1-7008247537	St. Soldier Group of Institutions	Jalandhar	Doaba
7	1-7009087016	Apeejay Institute of Management and Engineering Technical Campus	Jalandhar	Doaba
8	1-7009225337	Ramgarhia Institute of Engineering & Technology	Kapurthala	Doaba
9	1-7010294739	K.C. College of Engineering & Information Technology	Shahid Bhagat Singh Nagar	Doaba
10	1-7013230095	Doaba Khalsa Trust Group of Institutions	Shahid Bhagat Singh Nagar	Doaba
11	1-7015914994	Rayat Group Of Institutions	Shahid Bhagat Singh Nagar	Doaba
12	1-7003008471	D.A.V. Institute of Engineering & Technology	Jalandhar	Doaba

13	1-7003532189	C.T. Instiutte of Engineering, Management & Technology	Jalandhar	Doaba
14	1-7008540377	Lyallpur Khalsa College Technical Campus	Jalandhar	Doaba
15	1-7009602504	Guru Nanak Institute of Engineering & Management	Hoshiarpur	Doaba
16	1-7010598918	Faculty of Engineering	Kapurthala	Doaba
17	1-7012871912	Modern Group of Colleges	Hoshiarpur	Doaba

Table 3.8 List of AICTE Recognized Engineering Institutions in Malwa Region as per AICTE (2020-2021):

S.No.	Aicte ID	Name	District	Region
1	1-7002503996	Shaheed Bhagat Singh State Technical Campus	Firozpur	Malwa
2	1-7003388285	Shaheed Udham Singh College of Engineering & Technology	Mohali	Malwa
3	1-7003508897	Ram Devi Jindal Educational Charitable Society Group of Instiutions	Mohali	Malwa
4	1-7003601395	C.G.C. College of Engineering	Mohali	Malwa
5	1-7003877861	Lala Lajpat Rai Institute of Enggneering & Technology	Moga	Malwa
6	1-7003962896	BIS College of Engineering & Technology	Moga	Malwa
7	1-7004722460	Doaba Institute of Engg. & Tech.	S.A.S Nagar	Malwa
8	1-7004953922	Quest Infosys Foundation Group of Institutions	Mohali	Malwa
9	1-7006411402	Desh Bhagat Foundation Group of Institutions, Ferozpur Road Moga	Moga	Malwa
10	1-7006540372	G.G.S. College of Modern Technology	Mohali	Malwa

11	1-7008157668	Guru Nanak Dev Engineering College	Ludhiana	Malwa
12	1-7008178702	Indo Global College of Engineering	Mohali	Malwa
13	1-7008571954	Gulzar College of Engineering	Ludhiana	Malwa
14	1-7008768312	Baba Farid College of Engineering & Technology	Bathinda	Malwa
15	1-7008961977	Swami Vivekanand Institute of Engg. & Tech.	Patiala	Malwa
16	1-7009182600	Guru Ram Dass Institute of Engineering & Technology	Bathinda	Malwa
17	1-7009387332	Punjab College of Engineering & Technology	Mohali	Malwa
18	1-7010336152	Thapar Institute of Engineering and Technology	Patiala	Malwa
19	1-7010663928	University Institute of Engineering (UIE)	Mohali	Malwa
20	1-7011309086	Giani Zail Singh Campus College of Engineering and Technology	Bathinda	Malwa
21	1-7013121955	Aklia Educational and Research Society Group of Institutions	Bathinda	Malwa
22	1-7013195163	Gulzar Group of Institutions	Ludhiana	Malwa
23	1-7013255435	Sus Engineering College	S.A.S Nagar	Malwa
24	1-7022067819	Universal Group of Institutions (Universal School Of Engg.)	Mohali	Malwa
25	1-7185113832	Radiant Institute of Engineering & Technology	Firozpur	Malwa

26	1-7001793476	Asra College of Engineering & Technology	Sangrur	Malwa
27	1-7002501571	Baba Banda Singh Bahadur Engineering College	Fatehgarh Sahib	Malwa
28	1-7002646187	Chandigarh Engineering College	Mohali	Malwa
29	1-7003072345	Baba Hira Singh Bhattal Institute of Engineering and Technology	Sangrur	Malwa
30	1-7003118797	Ludhiana College Of Engineering & Technology	Ludhiana	Malwa
31	1-7003174976	Ghubaya College Of Engineering & Technology	Firozpur	Malwa
32	1-7003339621	Swift Technical Campus	Patiala	Malwa
33	1-7003621257	Sant Longowal Institute Of Engineering & Technology	Sangrur	Malwa
34	1-7004003560	Aryans College of Engineering (ACE)	Patiala	Malwa
35	1-7004798772	Pcte Institute of Engineering And Technology	Ludhiana	Malwa
36	1-7008368295	Sri Sukhmani Institute of Engineering & Technology	S.A.S Nagar	Malwa
37	1-7008911124	K.C.T. College of Engineering & Technology	Sangrur	Malwa
38	1-7009050586	University Institute of Emerging Technologies (UIET)	Mohali	Malwa
39	1-7009702945	Aryabhatta Group of Institutes	Barnala	Malwa
40	1-7009816000	Chandigarh Engineering College	Mohali	Malwa
41	1-7010917234	Guru Kashi University	Bathinda	Malwa
42	1-7011040314	Malout Institute of Management And Information Technology	Mukatsar	Malwa

43	1-7012996675	RIMT-Institute of Engineering And Technology	Fatehgarh Sahib	Malwa
44	1-7013077566	Ludhiana Group of Colleges	Ludhiana	Malwa
45	1-7013229319	Bhutta College of Engineering & Technology	Ludhiana	Malwa
46	1-7013235490	Bharat Group of Colleges	Mansa	Malwa
47	1-7013301326	Bahra Group of Institution	Patiala	Malwa
48	1-7013333058	Bhai Gurdas Institute of Engineering & Technology	Sangrur	Malwa
49	1-7022194079	Swami Parmanand College of Engg & Tech	Mohali	Malwa

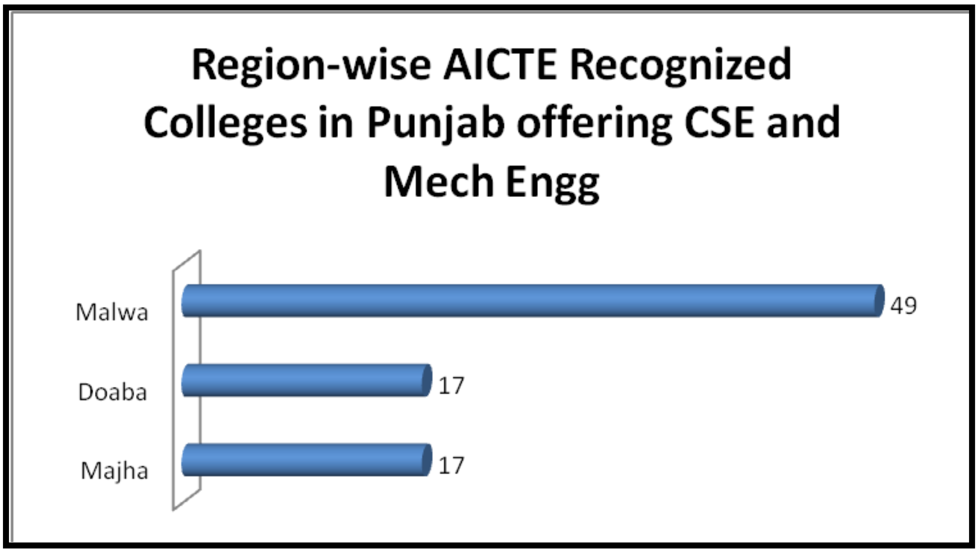


Figure 3.12 **Region-wise Distribution of AICTE Recognized Institutions Offering Computer Science and Mechanical Streams of Engineering in Punjab**

Table 3.9 List of Institutions Offering Computer Science and Mechanical Engineering in the Majha Region of Punjab – Sampling Frame of Majha Region:

S.No.	Aicte ID	Name	District	Region
1	1-7003159712	Sai Institute of Engineering & Technology	Amritsar	Majha

2	1-7003199822	Global Group of Institutes	Amritsar	Majha
3	1-7003409486	Shiv Shankar Institute of Engineering and Technology	Taran Taran	Majha
4	1-7004861580	Radical Technical Institute	Amritsar	Majha
5	1-7004949055	Baba Kuma Singh Ji Engg College	Amritsar	Majha
6	1-7008764885	Swami Sarvanand Institute of Engineering & Technology	Gurdaspur	Majha
7	1-7009811146	Beant College of Engineering & Technology	Gurdaspur	Majha
8	1-7013161156	Khalsa College of Engineering & Technology	Amritsar	Majha
9	1-7013175923	Sukhjinder Technical Campus	Gurdaspur	Majha
10	1-7013317304	Amritsar College of Engineering & Technology	Amritsar	Majha
11	1-7001875358	Aman Bhalla Institute of Engineering and Technology	Gurdaspur	Majha
12	1-7002909003	S.Sukhjinder Singh Engineering & Technology College	Gurdaspur	Majha
13	1-7005072724	Satyam Institute Of Engineering & Technology	Amritsar	Majha
14	1-7009583698	Tawi Engineering College	Gurdaspur	Majha
15	1-7012909478	Golden College Of Engineering & Technology	Gurdaspur	Majha
16	1-7012990033	M K Education Societie's Group of Institutions	Amritsar	Majha
17	1-7015891644	Sri Sai College Of Engg. & Tech	Gurdaspur	Majha
18	UGC University	Faculty of Engineering and Technology, Guru Nanak Dev University	Amritsar	Majha

Table 3.10 List of Institutions Offering Computer Science and Mechanical Engineering in the Doaba Region of Punjab - – Sampling Frame of Doaba Region:

:S.No.	AICTE ID	Name	District	Region
1	1-7002505328	Institute of Engineering & Technology	Rupnagar	Doaba
2	1-7003476133	C.T. Institute of Technology	Jalandhar	Doaba
3	1-7003728443	Rayat Bahra Institute of Engineering And Nano-Technology	Hoshiarpur	Doaba
4	1-7003830422	Global College of Engineering And Technology	Rupnagar	Doaba
5	1-7006832870	Anand College of Engineering & Management	Kapurthala	Doaba
6	1-7008247537	St. Soldier Group of Institutions	Jalandhar	Doaba
7	1-7009087016	Apeejay Institute of Management And Engineering Technical Campus	Jalandhar	Doaba
8	1-7009225337	Ramgarhia Institute of Engineering & Technology	Kapurthala	Doaba
9	1-7010294739	K.C. College of Engineering & Information Technology, Nawanshahr	Shahid Bhagat Singh Nagar	Doaba
10	1-7013230095	Doaba Khalsa Trust Group of Institutions - Faculty Of Engineering	Shahid Bhagat Singh Nagar	Doaba
11	1-7015914994	Rayat Group of Institutions , Ropar	Shahid Bhagat Singh Nagar	Doaba
12	1-7003008471	Dav Institute of Engineering & Technology	Jalandhar	Doaba
13	1-7003532189	C.T. Instiutte of Engineering, Management & Technology	Jalandhar	Doaba
14	1-7008540377	Lyallpur Khalsa College Technical Campus	Jalandhar	Doaba
15	1-7009602504	Guru Nanak Institute of Engineering & Management	Hoshiarpur	Doaba
16	1-7010598918	Faculty of Engineering	Kapurthala	Doaba
17	1-7012871912	Modern Group of Colleges	Hoshiarpur	Doaba

18	UGC University	D.A.V. University	Jalandhar	Doaba
19	UGC University	G.N.A University	Kapurthala	Doaba
20	UGC University	Lovely Professional University	Phagwara	Doaba
21	UGC University	Rayat Bahra University	Mohali	Doaba
22	UGC University	Sant Baba Bhag Singh University	Jalandhar	Doaba

Table 3.11 List of Institutions Offering Computer Science and Mechanical Engineering in the Malwa Region of Punjab - – Sampling Frame of Malwa Region::

S.No.	Aicte ID	Name	District	Region
1	1-7002503996	Shaheed Bhagat Singh State Technical Campus	Firozpur	Malwa
2	1-7003388285	Shaheed Udham Singh College of Engineering & Technology	Mohali	Malwa
3	1-7003508897	Ram Devi Jindal Educational Charitable Society Group of Instiutions	Mohali	Malwa
4	1-7003601395	Cgc College of Engineering	Mohali	Malwa
5	1-7003877861	Lala Lajpat Rai Institute of Enggneering & Technology	Moga	Malwa
6	1-7003962896	Bis College of Engineering & Technology	Moga	Malwa
7	1-7004722460	Doaba Institute of Engg. & Tech.	S.A.S Nagar	Malwa
8	1-7004953922	Quest Infosys Foundation Group of Institutions	Mohali	Malwa
9	1-7006411402	Desh Bhagat Foundation Group of Institutions	Moga	Malwa
10	1-7006540372	G.G.S. College of Modern	Mohali	Malwa

		Technology		
11	1-7008157668	Guru Nanak Dev Engineering College	Ludhiana	Malwa
12	1-7008178702	Indo Global College of Engineering	Mohali	Malwa
13	1-7008571954	Gulzar College of Engineering	Ludhiana	Malwa
14	1-7008768312	Baba Farid College of Engineering & Technology	Bathinda	Malwa
15	1-7008961977	Swami Vivekanand Institute of Engg. & Tech.	Patiala	Malwa
16	1-7009182600	Guru Ram Dass Institute of Engineering & Technology	Bathinda	Malwa
17	1-7009387332	Punjab College of Engineering & Technology	Mohali	Malwa
18	1-7010336152	Thapar Institute of Engineering and Technology	Patiala	Malwa
19	1-7010663928	University Institute of Engineering (UIE)	Mohali	Malwa
20	1-7011309086	Giani Zail Singh Campus College of Engineering and Technology	Bathinda	Malwa
21	1-7013121955	Aklia Educational And Research Society Group of Institutions	Bathinda	Malwa
22	1-7013195163	Gulzar Group of Institutions	Ludhiana	Malwa
23	1-7013255435	Sus Engineering College	S.A.S Nagar	Malwa
24	1-7022067819	Universal Group of Institutions (Universal School of Engg.)	Mohali	Malwa

25	1-7185113832	Radiant Institute of Engineering & Technology	Firozpur	Malwa
26	1-7001793476	Asra College of Engineering & Technology	Sangrur	Malwa
27	1-7002501571	Baba Banda Singh Bahadur Engineering College	Fatehgarh Sahib	Malwa
28	1-7002646187	Chandigarh Engineering College	Mohali	Malwa
29	1-7003072345	Baba Hira Singh Bhattal Institute of Engineering And Technology	Sangrur	Malwa
30	1-7003118797	Ludhiana College of Engineering & Technology	Ludhiana	Malwa
31	1-7003174976	Ghubaya College of Engineering & Technology	Firozpur	Malwa
32	1-7003339621	Swift Technical Campus	Patiala	Malwa
33	1-7003621257	Sant Longowal Institute of Engineering & Technology	Sangrur	Malwa
34	1-7004003560	Aryans College of Engineering (ACE)	Patiala	Malwa
35	1-7004798772	Pcte Institute of Engineering and Technology	Ludhiana	Malwa
36	1-7008368295	Sri Sukhmani Institute of Engineering & Technology	S.A.S Nagar	Malwa
37	1-7008911124	K.C.T. College of Engineering & Technology	Sangrur	Malwa
38	1-7009050586	University Institute of Emerging Technologies (UIET)	Mohali	Malwa
39	1-7009702945	Aryabhatta Group of Institutes	Barnala	Malwa

40	1-7009816000	Chandigarh Engineering College	Mohali	Malwa
41	1-7010917234	Guru Kashi University	Bathinda	Malwa
42	1-7011040314	Malout Institute of Management And Information Technology	Mukatsar	Malwa
43	1-7012996675	RIMT-Institute of Engineering and Technology	Fatehgarh Sahib	Malwa
44	1-7013077566	Ludhiana Group of Colleges	Ludhiana	Malwa
45	1-7013229319	Bhutta College of Engineering & Technology	Ludhiana	Malwa
46	1-7013235490	Bharat Group of Colleges	Mansa	Malwa
47	1-7013301326	Bahra Group of Institution	Patiala	Malwa
48	1-7013333058	Bhai Gurdas Institute of Engineering & Technology	Sangrur	Malwa
49	1-7022194079	Swami Parmanand College of Engg & Tech	Mohali	Malwa
50	UGC University	Punjabi University - Faculty of Engineering	Patiala	Malwa
51	UGC University	Chitkara University	Patiala	Malwa
52	UGC University	C.T. University - School of Engineering Technology	Ludhiana	Malwa
53	UGC University	Desh Bhagat University	Fatehgarh Sahib	Malwa
54	UGC University	Maharaja Ranjit Singh Punjab Technical University	Bathinda	Malwa

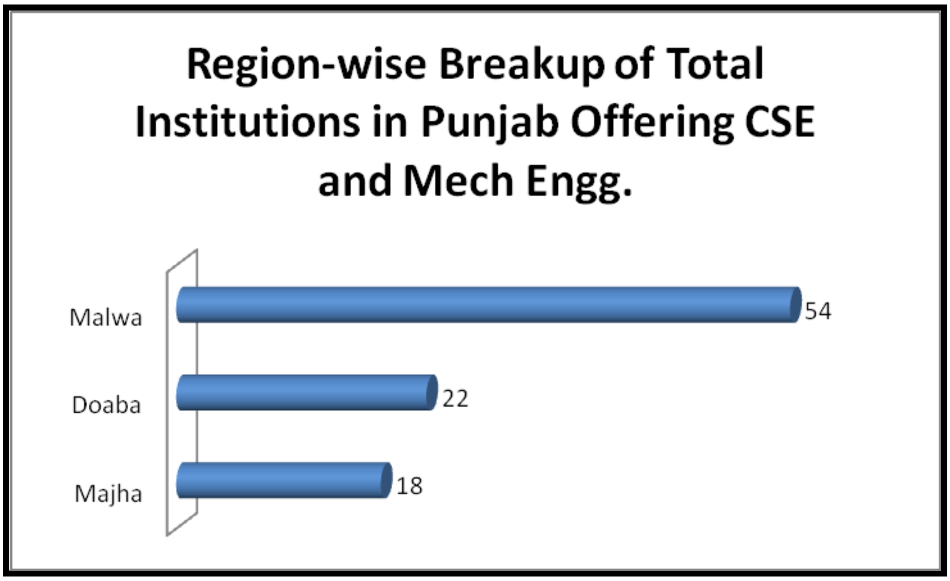


Figure 3.13 **Region-wise Breakup of Total Instituitions Offering Computer Science and Mechanical Engineering in Punjab**

3.3.1.3 Details of the Sample Selection:

The lucid definition of sampling frame is “the set of source materials from which the sample is selected” (Turner, 2003). That is why, the purpose of sampling frame is to render a means for selecting the specific members of the target population that are to be included in the survey. The unit of selection in the sampling frame is an individual institution / university offering Computer science and Mechanical engineering streams in its premises to students belonging to all the four years of duration of the engineering program. The area frame is used in the initial stage of sampling and the list frame is used in the last stage, as part of survey method of sampling design (Tuner, 2003). Under the area frame, all the units present in the geographical region are arranged in an order. These units should cover the geographical region, be populated, well mapped and must have clear boundaries. Coverage of the geographical region in totality is a vital criteria for obtaining a bona fide probability sample. Precise mapping and boundary help in identification of specific spot of data collection for the researcher. The figures of population help in estimation of sample size and for the calculation of the selection probabilities of sample.

The qualities of the sampling frame units of each of the regions, in this research are that the data is latest for the year of data collection, all the units in each of the regions, are arranged in numeric order and can be reached physically, and every unit is mentioned once without any redundancy. A latest sampling frame list possesses the other two of its properties, namely, completeness and accuracy. From such an area list of sampling frame, 10 percent of the units are randomly selected from each of the regions, to form the list frame or the list making the sample institutions to ultimately visit as part of final data collection. This exercise is according to the "*10 percent condition"* assumption of the Central Limit Theorem for using a normal distribution model in sampling (Berry and Lindgren, 1990; Neckerud, 2013). The details are shown below:

Table 3.12 Details of Sample Selection:

Region	**Total Institutions**	**10% of Total Institutions**	**Sample Institutions Visited for Data Collection (Round off Value)**
Majha	18	1.8	2
Doaba	22	2.2	2
Malwa	54	5.4	5
Punjab	94	9.4	**9**

3.3.2 Sample Composition:

The composition of the engineering undergraduate sample subjects from the three regions of Punjab is shown below:

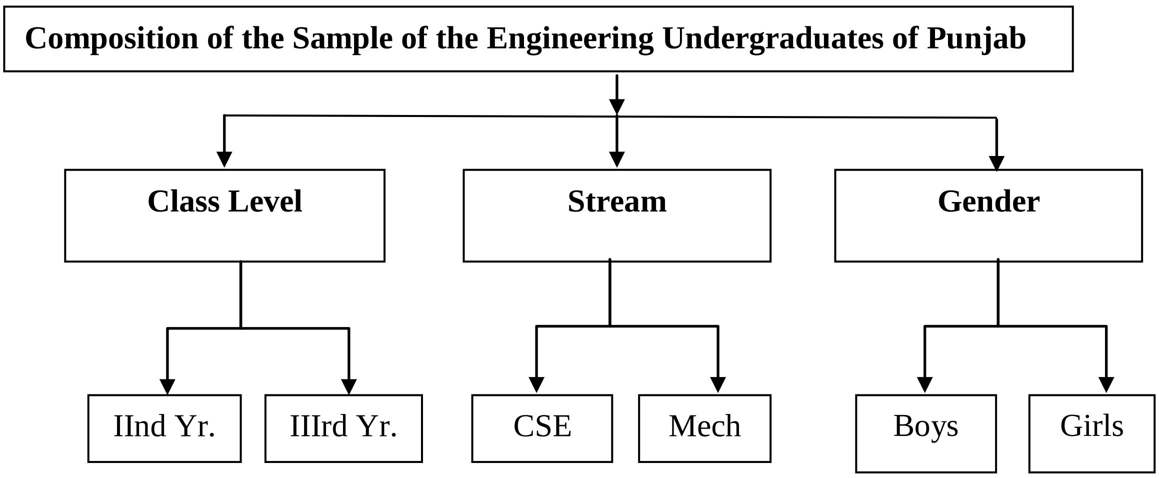


Figure 3.14 **Sample Composition**

3.3.3 Sampling Technique:

The theoretical basis for the selection of the sampling technique of this study was based on the Law of Statistical regularity and the Central limit theorem. According to the law of statistical regularity of probability, “a moderately large number of subjects selected at random from a large group are almost sure on the average to possess the characteristics of the large group”. It means that when sample subjects are chosen at random from a population, the sample then possesses the characteristics of the population. The large number of subjects ensures accuracy and stability of results too according to the law of inertia of large numbers, derived from the previous law. This postulate is then further supported by the central limit theorem, through which a mathematical means for estimating the population characteristics in terms of its parameters emerges. According to the central limit theorem, “if a random sample is drawn from any population, the sampling distribution of the sample mean is approximately normal for sufficiently large sample size”Kwak and Kim (2017). Without this fundamental theorem of modern Statistics, the parametric tests would not exist, which are based on the assumption that it is possible to determine the fixed parameters of a population using the sample data, using inferential statistics. Since the heterogeneous population of engineering students from IInd and IIIrd years of computer science and mechanical engineering streams in the large geographical area of the Punjab state was to be studied, the stratified random proportionate type sampling technique was used to select the subjects to form the sample from the sampling frame in this study. The chosen sampling technique also complimented the presence of unequal number of total engineering institutions in the three regions (Majha (18), Doaba (22) and Malwa (54)) of the Punjab state.

3.3.4 Sample:

Engineering students from IInd and IIIrd years of computer science and mechanical engineering streams belonging to 9 engineering institutions of Punjab, were selected as the sample as per the sampling design. The average age of the participants was 19.5 years which brought homogeneity among the subjects at the stratum level.The researcher visited 10 % of the total number of institutions (as per the assumptions of the Central Limit Theorem) in each of three regions (Strata), Majha, Doaba and

Malwa of Punjab state, to proportionately represent each of the strata regions without any overlapping, consistent with proportionate type of stratified random sampling, with details shown below:

<table>
<tr><th colspan="24">Table 3.13 Universities / Institutions in Punjab – 94 as per UGC and AICTE (2020-2021)</th></tr>
<tr><th colspan="8">Majha Region (Strata) - 2</th><th colspan="8">Doaba Region (Strata) - 2</th><th colspan="8">Malwa Region (Strata) - 5</th></tr>
<tr><td colspan="4">IInd Yr.</td><td colspan="4">IIIrd Yr.</td><td colspan="4">IInd Yr.</td><td colspan="4">IIIrd Yr.</td><td colspan="4">IInd Yr.</td><td colspan="4">IIIrd Yr.</td></tr>
<tr><td colspan="2">CSE</td><td colspan="2">Mech</td><td colspan="2">CSE</td><td colspan="2">Mech</td><td colspan="2">CSE</td><td colspan="2">Mech</td><td colspan="2">CSE</td><td colspan="2">Mech</td><td colspan="2">CSE</td><td colspan="2">Mech</td><td colspan="2">CSE</td><td colspan="2">Mech</td></tr>
<tr><td>B</td><td>G</td><td>B</td><td>G</td><td>B</td><td>G</td><td>B</td><td>G</td><td>B</td><td>G</td><td>B</td><td>G</td><td>B</td><td>G</td><td>B</td><td>G</td><td>B</td><td>G</td><td>B</td><td>G</td><td>B</td><td>G</td><td>B</td><td>G</td></tr>
<tr><td colspan="4">Students of average age 19.5 years (Stratum)</td><td colspan="4">Students of average age 19.5 years (Stratum)</td><td colspan="4">Students of average age 19.5 years (Stratum)</td><td colspan="4">Students of average age 19.5 years (Stratum)</td><td colspan="4">Students of average age 19.5 years (Stratum)</td><td colspan="4">Students of average age 19.5 years (Stratum)</td></tr>
</table>

The names of the 9 institutions (two, two and five institutions from Majha, Doaba and Malwa regions respectively) were selected using random number generation.

3.3.5 Sampling Procedure:

The investigator visited three engineering institutions, two in Majha region and one in Doaba region, explained the purpose of the visit and sought permission of the Head of the computer science and mechanical engineering departments to collect data. The investigator administered questionnaires on the subjects. The investigator gave clear instructions regarding filling of the responses in different questionnaire to the engineering undergraduates. Due to COVID-19 epidemic outbreak, the mode of data collection was changed to online. A google form link of the questionnaire was created and shared with the head of the left over engineering institutions, to be further shared with the target subjects to cover data collection in the Doaba and Malwa regions. After that, scoring was done according to responses of the respondents. Statistical techniques were employed on obtained scores of data to get results.

3.4 Determination of Sample Size:

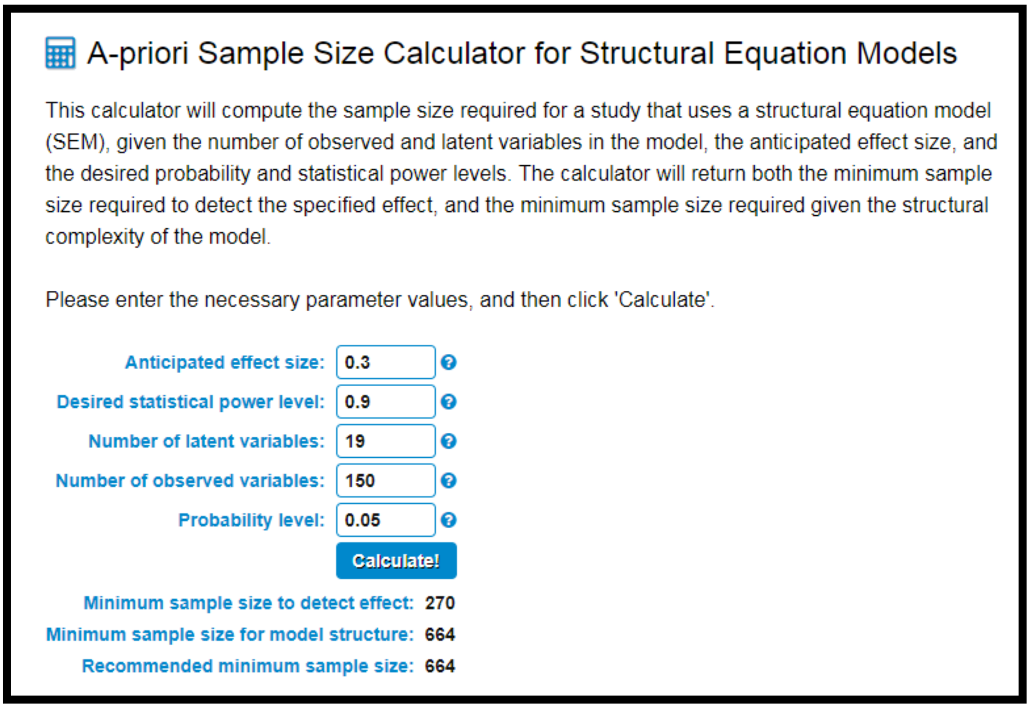


Figure 3.5 **Initial Sample Size Estimation**

Remark: The sample size can change post scale purification of the tools. Also, according to Cheung and Rensvold (2002), the use of alternative fit indices as the fit criteria is becoming a common practice, and in this context, with adequate power assumed, the sample size is a less important factor in the achievement of measurement invariance of models. This is owing to the fact that alternative fit indices are less affected by sample size (Putnick and Bornstein, 2016).

The final sample size determined post validation of all tools:

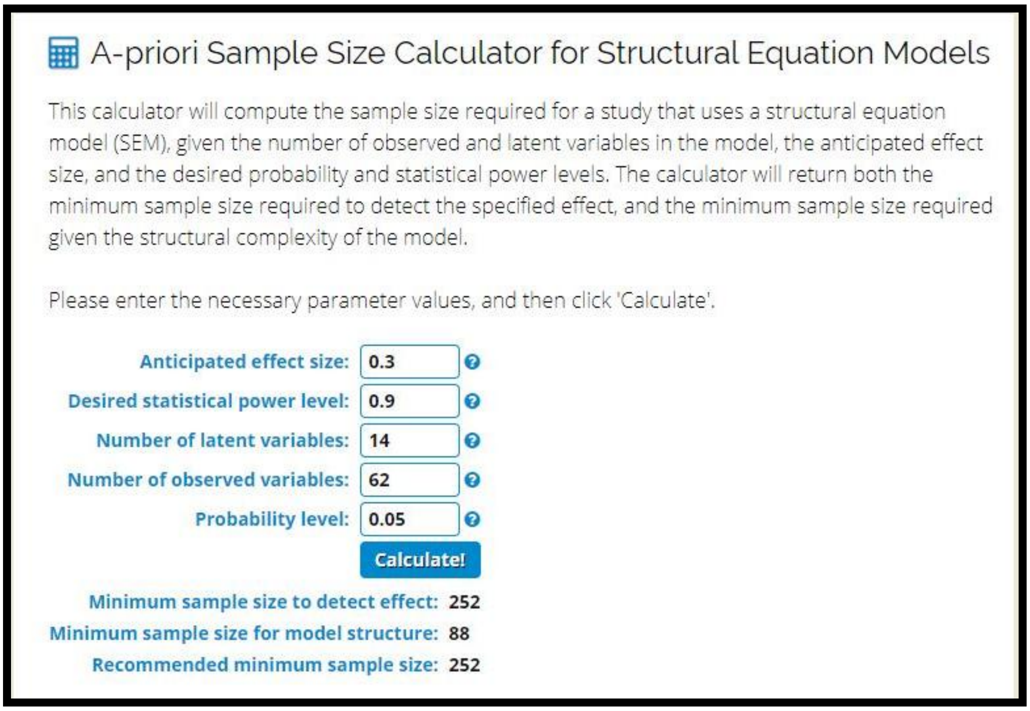


Figure 3.6 **Final Sample Size Estimation**

Source: Soper (2018) – Online calculator based on the works of Cohen (1988) and Westland (2010).

3.5 Tools Used in the Study:

The following tools were administered to conduct the present study:

Table 3.14 List of Tools Used in the Study:

S.No.	SRL Variable	SRL St.	Leading Theory of Origin	Proposed by	Tool of Origin
1.	Critical Thinking	COG	Social cognitive theory	Bandura (1986)	MSLQ - R by Jackson (2018)
2.	Organization				
3.	Self Evaluation	META			
4.	Self Recording				
5.	Planning				
6.	Self Efficacy	MOT- MB			
7.	Goal Orientation				
8.	Academic Intrinsic Motivation		Self Determination theory	Deci and Ryan (1985)	AMS – 28 by Vallerand et al. (1992)
9.	Academic Delay of Gratification	MOT - VOL	Hot-cool systems theory	Mischel (1981)	ADGS by Bembenutty and Karabenick (1996)
10.	Academic Procrastination		Temporal motivation theory	Steel and Konig (2006)	APS – SF by Yockey (2016)
11.	Future Time Perspective		Socioemotional selectivity theory	Carstensen and Lang (1996)	ZTP-SF by Orosz (2015)
12.	Reappraisal	EMO	Process theory	Gross (1998)	AERQ by Buric et al. (2016)
13.	Suppression				
14.	Time and study environment	BEH	Social cognitive theory	Bandura (1986)	MSLQ - R by Jackson (2018)

3.6 Statistical Techniques -Chronology of Application and their Software:

1. Outlier Verification using SPSS Statistics Ver.23.0:
    - Mahalanobis distance for detection of outliers
2. Reliability Analysis using FACTOR / RStudio:
    - Cronbach's alpha,
    - Polychoric Omega for Ordinal Likert-scale based Responses.
3. Descriptive statistics using SPSS Statistics Ver.23.0:
    - Mean
    - Standard Deviation
    - Inter-item Correlation
4. DIF of Items using EasyDIF – MI of Items across Gender
5. PIRT Analysis of Items using R/RStudio:
    - ICC
    - TCC
    - OCC
    - IIC
6. NIRT Analysis of Items using TestGraph98:
    - ICC
    - OCC
7. Component wise Factor Analysis (EFA / CFA) of the factor structures using SPSS Statistics / AMOS Ver.23.0
8. Network Psychometrics based tool / model validation using R/RStudio
    - Exploratory Graph Analysis (EGA)
    - Ordinal WLSMV based Confirmatory Factor Analysis
    - Structural Consistency
9. Ant Colony Optimization (ACO) based scale purification using R/RStudio
10. Latent Profile Analysis (LPA) using tidyLPA package of R/RStudio.
11. CTT Analysis of Items using SPSS Statistics and SPSS AMOS Ver 23.0
12. CFA of the Alternate Models for determining the position of Volition in the revised model and its validation using SPSS AMOS Ver.23.0
13. Power Analysis using R/RStudio

14. Measurement Invariance (MI) testing Category-1 of the complete model with respect to gender, batch and stream using SPSS AMOS Ver.23.0

Conclusion: The next chapter discusses the statistical techniques using which the collected data was analyzed, interpreted and finally reported as part of this research study. The selection of the applied statistical techniques under descriptive and inferential statistics and their effective are based on the designed methodology discussed in detail in the preceeding chapter. The final chapter builds on the findings of the succeeding chapter and would discuss the implications of these findings on self regulated learning based engineering academics.

CHAPTER 4
DATA ANALYSIS

4.1 Introduction

This chapter presents the details of the analytical techniques applied on the gathered data, both during the pilot study phase to validate the instruments selected for the study and during final data collection phase to achieve the research objectives, along with the interpretation of the collected data.

As a part of justification of the selected techniques, the literature review studies of relevance were also mentioned as and when the context appeared. Apart from the conventional techniques of analysis, certain state of the art, less known and evolving techniques of data analysis were also administered in this research.For instance, the short coming of the Pearson correlation based covarience matrix in properly extracting the factors through exploratory factor analysis, lead to the introduction of Polychoric correlation matrix based Network psychometric exploratory graph analysis of factor extraction. Also, the erronous Cronbach alpha is reported along side the new estimate of Polychoric Omega reliability, further refined through the estimation of structural consistency over the internal consistency based reliability estimation of the scales in this study.

In the succeeding sections, the validation of the seven tools of the study, and data analysis justifying the stated objectives of the study are presented.

4.2 Validation of the Instruments of the Research Study:

4.2.1 Validation of the Parsimonious Version of the Motivated Strategies of Learning Questionnaire in the Indian Context:

The Motivated Strategies for Learning Questionnaire (MSLQ) developed by Pintrich et al. (1991) is one of the vastly administered tool for measuring self regulated component in the college going students across the world. Several countries administered this tool on college going students for validation and adaption in their local context. Jackson (2018) developed the parsimonious version of this scale in the American context. The present study compared the psychometric properties of the items and sub-scales of this instrument and conducted scale purification to extract a parsimonious version of it in the Indian context. 1799 college going students (1144 girls and 655 boys) from the three regions, Majha, Doaba and Malwa, of Punjab at undergraduate and postgraduate levels were the participants of the study as shown below:

Table 4.1 Distribution of MSLQ Sample Subjects with respect to Region

Region	N
Majha	620
Malwa	570
Doaba	609

TABLE 4.2 Distribution of the MSLQ Sample Subjects with respect to Level

Level	N
Undergraduate	1009
Postgraduate	790

The details of the 15 sub-scales and the distribution of 81 items among them are shown below as in the original scale:

Table 4.3 The Motivated Strategies for Learning Questionnaire

S.No.	Scale	Variable	Items
1.	Motivation	Intrinsic Goal Orientation	1,16,22,24 (4)
2.		Extrinsic Goal Orientation	7,11,13,30 (4)
3.		Task Value	4,10,17,23,26,27 (6)
4.		Control on Learning Belief	2,9,18,25(4)
5.		Self-Efficacy for Learning and Performance	5,6,12,15,20,21,29,31(8)
6.		Test Anxiety	3,8,14,19,28 (5)
7.	Learning Strategy	Rehearsal	39,46,59,72 (4)
8.		Elaboration	53, 62, 64,67, 69,81(6)

9.		Organization	32,42,49,63 (4)
10.		Critical Thinking	38,47,51,66,71 (5)
11.		Meta-cognitive self regulation	33R,36,41,44,54,55,56,57R,61,76,78.79 (12)
12.		Time Management and Study Environment	35,43,52R, 65,70,73,77R,80R (8)
13.		Effort Regulation	37R, 48, 60R,74 (4)
14.		Peer Learning	34,35,50 (3)
15.		Help Seeking	40R,58,68,75 (4)

The details of the 11 sub-scales and the distribution of 49 items among them are shown below as in the parsimonious scale:

Table 4.4The Motivated Strategies and Learning Questionnaire - Revised

S.No.	Scale	Variable	Items with Remarks
1.	Motivation	Intrinsic Goal Orientation	1,16,22,24 (4) as in Original scale
2.		Extrinsic Goal Orientation	Sub-scale Eliminated
3.		Task Value	4,17,23,26,27 (5); Item 10 of the original scale removed
4.		Control on Learning Belief	2,9,18,25(4) as in Original scale
5.		Self-Efficacy for Learning and Performance	5,6,12,15,20,21,29,31(8) as in Original scale
6.		Test Anxiety	Sub-scale Eliminated
7.	Learning Strategy	Rehearsal	39,46,59,72 (4) as in Original scale
8.		Elaboration	53, 62, 64, 69,81(5); Item 67 of the original scale eliminated
9.		Organization	42,49 (2); Item 32 and 49 of the original scale eliminated
10.		Critical Thinking	47,51,66,71 (5); Item 38 of the original scale eliminated
11.		Meta-cognitive self	41,44,54,55,57R,76 (6); Items 33R,36, 56,61,

		regulation	78.79 of the original scale eliminated
12.		Time Management and Study Environment	35,43, 65,70 (4); Items 52R, 73,77R,80R of the original scale eliminated
13.		Effort Regulation	48, 74 (2) ; Items 37R and 60R of the original scale eliminated
14.		Peer Learning	Sub-scale Eliminated
15.		Help Seeking	Sub-scale Eliminated

The analysis of the estimates of reliability (Cronbach's Alpha) of the sub-scales in the 1991 and 2018 versions of the MSLQ are shown below for comparison:

Table 4.5 Reliability Analysis of MSLQ and Parsimonious MSLQ - R:

S.No.	Scale	Variable	Reliability MSLQ (1991) - Cronbach's Alpha	Reliability Parsimonious MSLQ – R (2018) – Cronbach's Alpha
1.	Motivation	Intrinsic Goal Orientation	0.74	0.67
2.		Extrinsic Goal Orientation	0.62	Scale Eliminated
3.		Task Value	0.9	0.88
4.		Control on Learning Belief	0.68	0.73
5.		Self-Efficacy for Learning and Performance	0.93	0.92
6.		Test Anxiety	0.8	Scale Eliminated
7.	Learning Strategy	Rehearsal	0.69	0.7
8.		Elaboration	0.76	0.8
9.		Organization	0.64	0.61
10.		Critical Thinking	0.8	0.8
11.		Meta-cognitive self regulation	0.79	0.77
12.		Time Management and Study Environment	0.76	0.75

13.		Effort Regulation	0.69	0.66
14.		Peer Learning	0.76	Scale Eliminated
15.		Help Seeking	0.52	Scale Eliminated

During the analysis of the psychometrics of the sub-scales, they were dealt separately since they can either be treated collectively or in modular manner during data collection (Pintrich et al., 1991).

After the evaluation of the measures of central tendency like mean, dispersion like standard deviation and asymmetry like skewness and kurtosis under descriptive statistics, exploratory factor analysis technique on each of the sub-scales were conducted to ensure its unidimensionality and measure the total variance explained. The factor sturucture is confirmed using confirmatory factor analysis through factor loadings and goodness of fit indices estimates. Then, reliability analysis of the sub-scale of the original scale is found through the Cronbach's alpha, item-total correlation and greatest lower bound reliability. These estimates of the revised MSLQ (2018) are found and compared using AIC and BIC estimates with the original MSLQ (1991) subscale. The better model is retained with at least three items in it for making it part of the Indian version of MSLQ scale. The mentioned logic is extended to the rest of the sub-scales as shown below:

4.2.1.1 Intrinsic Goal Orientation Scale – Psychometrics:

Table 4.6 Descriptive Statistics of Intrinsic Goal Orientation Scale:

Item	Mean	Standard Deviation	Skewness	Kurtosis	Standard Error
1	5.047	1.743	-0.592	-0.561	0.041
16	4.922	1.553	-0.450	-0.388	0.036
22	5.259	1.483	-0.650	-0.129	0.035
24	4.803	1.595	-0.496	-0.335	0.037

Table 4.7 Inter-Item Correlation Matrix of Intrinsic Goal Orientation Scale:

Correlation Matrix[a]

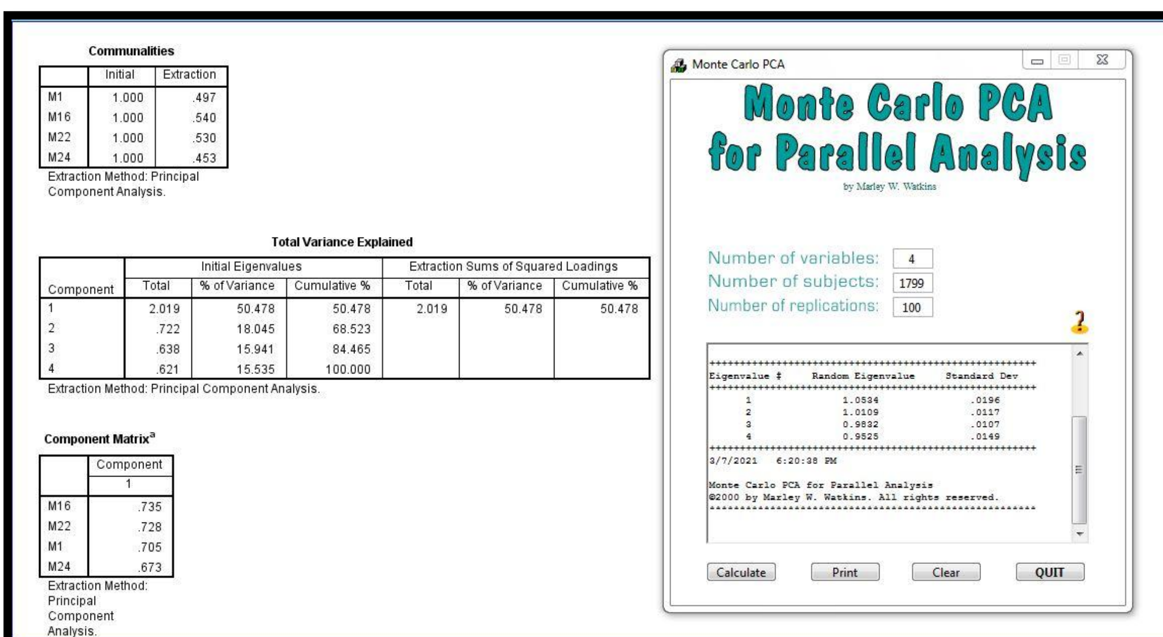
		M1	M16	M22	M24
Correlation	M1	1.000	.366**	.356**	.282**
	M16	.366**	1.000	.365**	.335**
	M22	.356**	.365**	1.000	.331**
	M24	.282**	.335**	.331**	1.000

a. Determinant = .578

b. ** - Correlation is significant at the **0.01** level (1-tailed)

Table 4.8 KMO and Barlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.734
Bartlett's Test of Sphericity	Approx. Chi-Square	985.996
	df	6
	Sig.	.000



Communalities

	Initial	Extraction
M1	1.000	.497
M16	1.000	.540
M22	1.000	.530
M24	1.000	.453

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.019	50.478	50.478	2.019	50.478	50.478
2	.722	18.045	68.523			
3	.638	15.941	84.465			
4	.621	15.535	100.000			

Extraction Method: Principal Component Analysis.

Component Matrix[a]

	Component 1
M16	.735
M22	.728
M1	.705
M24	.673

Extraction Method: Principal Component Analysis.

Figure 4.1 **Total Variance Explained of Intrinsic Goal Orientation Scale**

The obtained eigen value 2.019 is higher than the random eigen value of 1.0534 generated by the parallel analysis software, confirming the unidimensionality of Intrinsic goal orientation sub-scale with 50.478 percent of its total variance explained.

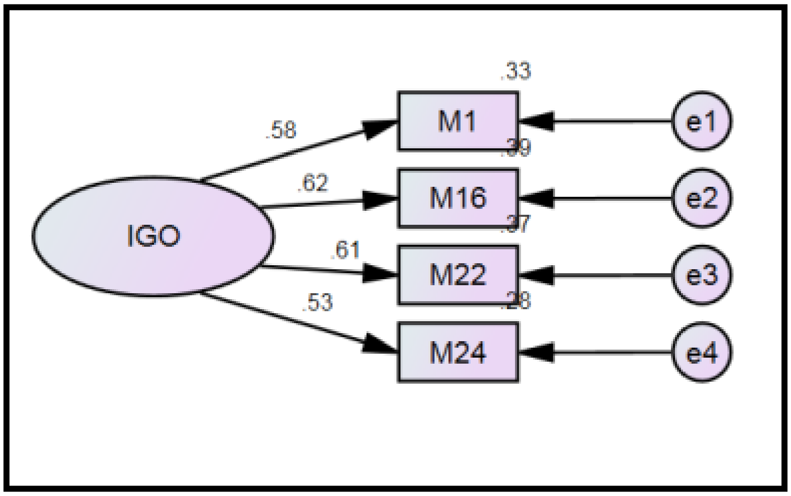


Figure 4.2 **Factor Loadings of Intrinsic Goal Orientation Scale from Confirmatory Factor Analysis:**

Table 4.9 Goodness of Fit Estimates of Intrinsic Goal Orientation Scale

Estimates	**CMIN/DF**	**RMR**	**GFI**	**TLI**	**CFI**	**RMSEA**
Benchmark	<3	<0.08	>0.93	>0.93	>0.93	<0.08
Magnitude	1.872	0.025	0.999	0.995	0.998	0.022

The revised MSLQ (2018) also has the same number of items. The magnitude of the obtained estimates of goodness of fit is well within their desirable limits, indicating the stability of the factor structure of intrinsic goal orientation scale to be intact.

Table 4.10 Inter-Item Statistics:

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted

M1	14.984	12.068	.445	.205	.610
M16	15.109	12.763	.480	.231	.585
M22	14.772	13.214	.472	.223	.592
M24	15.228	13.165	.414	.176	.628

Table 4.11 Reliability of Intrinsic Goal Orientation Scale:

Cronbach's α	Guttman's λ 2	McDonald's Ω	Composite Reliability	GLB
0.672	0.671	0.673	0.676	(0.688,1)

Kyriazos et al. (2018) mentioned the suggestion of Kline (1999) that for psychological constructs, the estimate of internal consistency reliability Cronbach alpha could be as low as 0.6. While the true reliability would lie within the confidence interval of 0.688 and 1, the point estimates are well above the acceptable benchmark for the intrinsic goal orientation scale, indicating its fair reliability.

4.2.1.2 Extrinsic Goal Orientation Scale – Psychometrics:

Table 4.12 Descriptive Statistics of Extrinsic Goal Orientation Scale:

Item	Mean	Standard Deviation	Skewness	Kurtosis	Standard Error
7	4.928	1.735	-0.572	-0.547	0.041
11	5.345	1.596	-0.705	-0.365	0.038
13	5.188	1.575	-0.705	-0.176	0.037
30	5.043	1.69	-0.638	-0.35	0.040

Table 4.13 Inter-Item Correlation Matrix

Correlation Matrix[a]

		M7	M11	M13	M30
Correlation	M7	1.000	.382**	.325**	.286**
	M11	.382**	1.000	.464**	.364**
	M13	.325**	.464**	1.000	.332**
	M30	.286**	.364**	.332**	1.000

a. Determinant = .530

b. ** - Correlation is significant at the **0.01** level (1-tailed)

Table 4.14 KMO and Barlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.734
Bartlett's Test of Sphericity	Approx. Chi-Square	1140.355
	df	6
	Sig.	.000

Table 4.15 Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.083	52.067	52.067	2.083	52.067	52.067
2	.715	17.870	69.936			
3	.676	16.895	86.831			
4	.527	13.169	100.000			

Extraction Method: Principal Component Analysis.

The obtained eigen value 2.083 is higher than the random eigen value of 1.0504 generated by the parallel analysis software, confirming the unidimensionality of Extrinsic goal orientation sub-scale with 52.067 percent of its total variance explained.

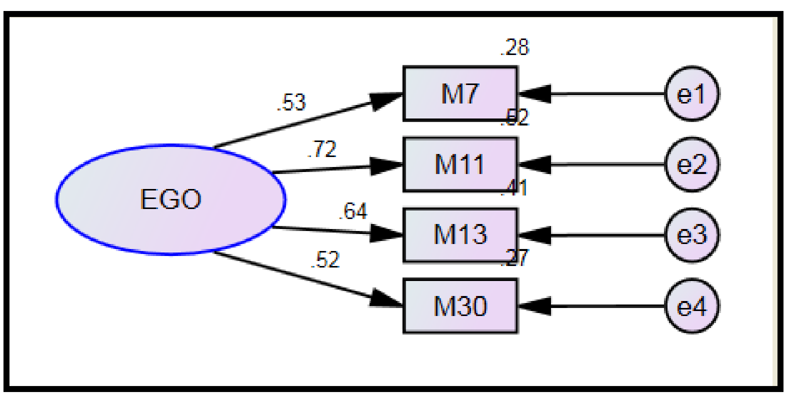


Figure 4.3 **Factor Loadings of Extrinsic Goal Orientation Scale from Confirmatory Factor Analysis**

Table 4.16 Goodness of Fit Estimates:

Estimates	**CMIN/DF**	**RMR**	**GFI**	**TLI**	**CFI**	**RMSEA**
Benchmark	<3	<0.08	>0.93	>0.93	>0.93	<0.08
Magnitude	0.824	0.018	1.000	1.001	1.000	0.000

The revised MSLQ (2018) deleted this scale due to its dismal performance psychometrically. However, in this study all the items displayed very good performance akin the original scale of 1991 and hence they were kept unchanged.

Table 4.17 Inter-Item Statistics:

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
M7	15.577	13.954	.430	.652
M11	15.160	13.573	.546	.577
M13	15.317	14.178	.495	.610
M30	15.462	14.269	.424	.655

Table 4.18 Reliability of Extrinsic Goal Orientation Scale:

Cronbach's α	Guttman's λ 2	McDonald's Ω	Composite Reliability	GLB
0.689	0.69	0.695	0.697	(0.704,1)

Kyriazos et al. (2018) mentioned the suggestion of Kline (1999) that for psychological constructs, the estimate of internal consistency reliability Cronbach alpha could be as low as 0.6. While the true reliability would lie within the confidence interval of 0.704 and 1, the point estimates are well above the acceptable benchmark for the extrinsic goal orientation scale, indicating its good reliability.

4.2.1.3Task Value Scale – Psychometrics:

Table 4.19 Descriptive Statistics of Task Value Scale:

Item	Mean	Standard Deviation	Skewness	Kurtosis	Standard Error
4	4.96	1.627	-0.567	-0.356	0.038
10	5.316	1.571	-0.817	-0.005	0.037
17	4.906	1.6	-0.578	-0.281	0.037
23	5.119	1.65	-0.723	-0.269	0.039
26	4.976	1.577	-0.577	-0.205	0.037
27	5.174	1.546	-0.633	-0.285	0.036

Table 4.20 Inter-Item Correlation Matrix:

Correlation Matrix[a]

		M4	M10	M17	M23	M26	M27
Correlation	M4	1.000	.352**	.348**	.320**	.323**	.296**
	M10	.352**	1.000	.364**	.469**	.315**	.403**
	M17	.348**	.364**	1.000	.409**	.461**	.394**
	M23	.320**	.469**	.409**	1.000	.401**	.507**
	M26	.323**	.315**	.461**	.401**	1.000	.478**
	M27	.296**	.403**	.394**	.507**	.478**	1.000

a. Determinant = .224

b. ** - Correlation is significant at the **0.01** level (1-tailed)

Table 4.21 KMO and Barlett's Test:

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.838
Bartlett's Test of Sphericity	Approx. Chi-Square	2689.280
	df	15
	Sig.	.000

Table 4.22 Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.957	49.288	49.288	2.957	49.288	49.288
2	.762	12.699	61.987			
3	.731	12.186	74.173			
4	.586	9.764	83.937			
5	.506	8.435	92.372			
6	.458	7.628	100.000			

Extraction Method: Principal Component Analysis.

The obtained Eigen value 2.957 is higher than the random eigen value of 1.0796 generated by the parallel analysis software, confirming the unidimensionality of task valuesub-scale with 49.288 percent of its total variance explained.

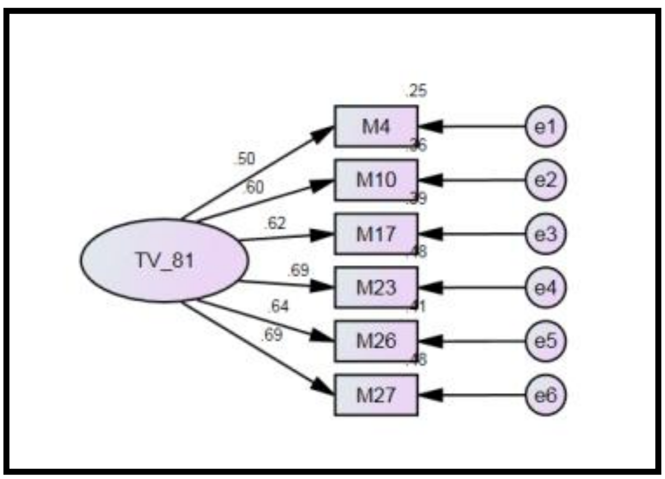


Figure 4.4 **Factor Loadings of Task Value Original Scale from Confirmatory Factor Analysis**

Table 4.23 Goodness of Fit Estimates – Original Scale:

Estimates	CMIN/ DF	RMR	GFI	TLI	CFI	RMSEA	AIC	BIC

Benchmark	<3	<0.08	>0.93	>0.93	>0.93	<0.08	-	-
Magnitude	13.33	0.087	0.978	0.931	0.959	0.083	143.968	209.908

The parsimonious scale of 2018 retained only five items from the original scale's 10 items. These items in the present study, items 4,17,23, 26 and 27, together explained 51.732 % variance under unidimensionality with the below factor structure:

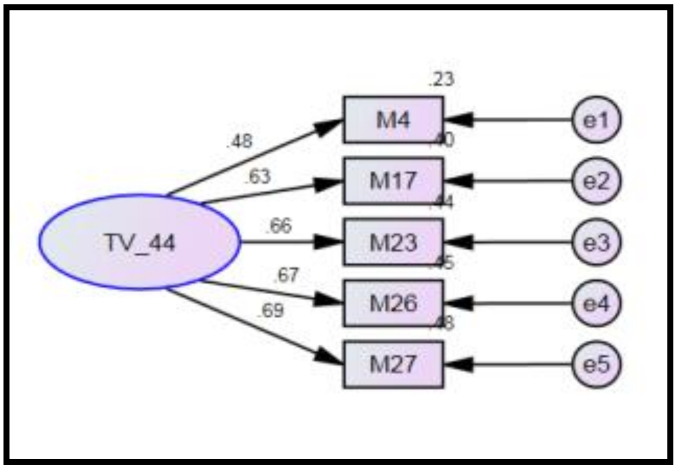


Figure 4.5 **Factor Loadings of Parsimonious Task Value Scale**

Table 4.24 Goodness of Fit Estimates – Parsimonious Scale:

Estimates	CMIN/DF	RMR	GFI	TLI	CFI	RMSEA	AIC	BIC
Benchmark	<3	<0.08	>0.93	>0.93	>0.93	<0.08	143.968	209.908
Magnitude	11.872	0.069	0.987	0.947	0.973	0.078	79.361	134.311

Since the AIC and BIC estimates of the 2018 MSLQ model of task value are smaller than the MSLQ 1991 model, the items of the parsimonious model are retained.

Table 4.25 Inter-Item Statistics:

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
M4	20.175	23.618	.422	.759

M17	20.229	22.134	.548	.716
M23	20.017	21.667	.557	.712
M26	20.160	22.060	.567	.709
M27	19.961	22.189	.574	.707

Table 4.26 Reliability of Task Value Scale:

Cronbach's α	Guttman's λ 2	McDonald's Ω	Composite Reliability	GLB
0.764	0.766	0.767	0.765	(0.796,1)

Kyriazos et al. (2018) mentioned the suggestion of Kline (1999) that for psychological constructs, the estimate of internal consistency reliability Cronbach alpha could be as low as 0.6. While the true reliability would lie within the confidence interval of 0.796 and 1, the point estimates are well above the acceptable benchmark for the intrinsic goal orientation scale, indicating its very good reliability.

4.2.1.4 Control on Learning Belief Scale – Psychometrics:

Table 4.27 Descriptive Statistics of Control on Learning Beliefs Scale:

Item	Mean	Standard Deviation	Skewness	Kurtosis	Standard Error
2	5.313	1.622	-0.788	-0.158	0.038
9	5.023	1.755	-0.646	-0.449	0.041
18	5.077	1.664	-0.673	-0.351	0.039
25	4.624	1.751	-0.467	-0.567	0.041

Table 4.28 Inter-Item Correlation Matrix

Correlation Matrix[a]

		M2	M9	M18	M25
Correlation	M2	1.000	.234**	.335**	.239**
	M9	.234**	1.000	.246**	.232**
	M18	.335**	.246**	1.000	.235**
	M25	.239**	.232**	.235**	1.000

a. Determinant = .724

b. ** - Correlation is significant at the **0.01** level (1-tailed)

Table 4.29 KMO and Barlett's Test:

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.683
Bartlett's Test of Sphericity	Approx. Chi-Square	580.699
	df	6
	Sig.	.000

Table 4.30 Total Variance Explained:

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1.763	44.081	44.081	1.763	44.081	44.081
2	.804	20.088	64.169			
3	.769	19.223	83.392			
4	.664	16.608	100.000			

Extraction Method: Principal Component Analysis.

The obtained eigen value 1.763 is higher than the random eigen value of 1.0535 generated by the parallel analysis software, confirming the unidimensionality of control on learning beliefssub-scale with 44.081 percent of its total variance explained.

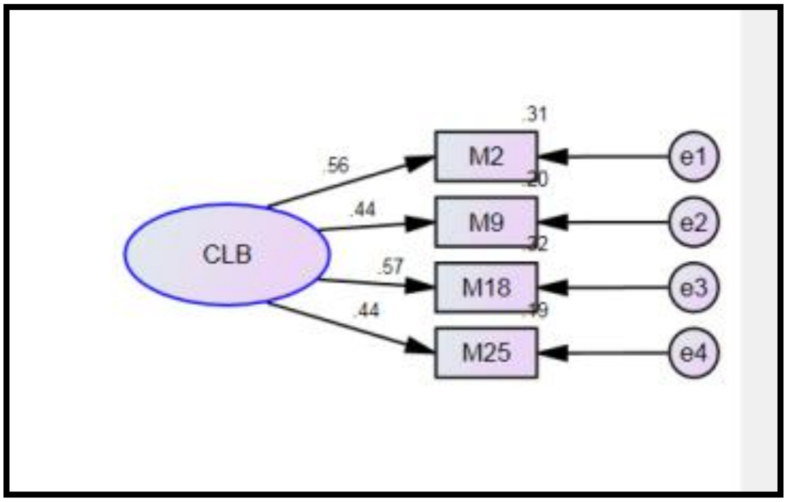


Figure 4.6 **Factor Loadings of Control on Learning Beliefs Scale**

Table 4.31 Goodness of Fit Estimates:

Estimates	**CMIN/DF**	**RMR**	**GFI**	**TLI**	**CFI**	**RMSEA**
Benchmark	<3	<0.08	>0.93	>0.93	>0.93	<0.08
Magnitude	3.193	0.043	0.998	0.977	0.992	0.035

Both the original and revised versions of the MSLQ scale have the same four items. The obtained fit estimates satisfy their desirable limits, establishing the construct validity of control on learning belief scale through the stability of its factor structure.

Table 4.32 Inter-Item Statistics:

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
M2	14.726	13.158	.382	.483
M9	15.016	13.019	.331	.524
M18	14.961	12.902	.386	.479
M25	15.415	13.065	.328	.526

Table 4.33 Reliability of Control on Learning Beliefs Scale:

Cronbach's α	Guttman's λ 2	McDonald's Ω	Composite Reliability	GLB
0.574	0.575	0.577	0.576	(0.597,1)

Kyriazos et al. (2018) mentioned the suggestion of Kline (1999) that for psychological constructs, the estimate of internal consistency reliability Cronbach alpha could be as low as 0.6. While the true reliability would lie within the confidence interval of 0.597 and 1, the point estimates are close to the acceptable benchmark for the control on learning belief scale, indicating its almost fair reliability.

4.2.1.5 Self Efficacy Scale – Psychometrics:

Table 4.34 Descriptive Statistics of Self Efficacy Scale:

Item	Mean	Standard Deviation	Skewness	Kurtosis	Standard Error
5	5.034	1.604	-0.646	-0.268	0.0378
6	4.668	1.574	-0.429	-0.392	0.0371
12	5.248	1.534	-0.711	-0.112	0.0362
15	4.775	1.538	-0.429	-0.337	0.03627
20	5.076	1.541	-0.581	-0.281	0.0363
21	5.301	1.522	-0.786	-0.006	0.0359
29	4.801	1.531	-0.49	-0.23	0.0361
31	5.043	1.501	-0.623	-0.077	0.0354

Table 4.35 Inter-Item Correlation Matrix:

Correlation Matrix[a]

		M5	M6	M12	M15	M20	M21	M29	M31
Correlation	M5	1.000	.321**	.345**	.321**	.375**	.339**	.279**	.321**
	M6	.321**	1.000	.336**	.359**	.296**	.304**	.291**	.293**
	M12	.345**	.336**	1.000	.367**	.391**	.458**	.310**	.340**
	M15	.321**	.359**	.367**	1.000	.337**	.324**	.324**	.324**
	M20	.375**	.296**	.391**	.337**	1.000	.466**	.363**	.390**
	M21	.339**	.304**	.458**	.324**	.466**	1.000	.328**	.377**
	M29	.279**	.291**	.310**	.324**	.363**	.328**	1.000	.404**

M31	.321**	.293**	.340**	.324**	.390**	.377**	.404**	1.000

a. Determinant = .160

b. ** - Correlation is significant at the **0.01** level (1-tailed)

Table 4.36 KMO and Barlett's Test:

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.887
Bartlett's Test of Sphericity	Approx. Chi-Square	3288.616
	df	28
	Sig.	.000

Table 4.37 Total Variance Explained:

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.429	42.858	42.858	3.429	42.858	42.858
2	.803	10.036	52.894			
3	.771	9.635	62.529			
4	.688	8.604	71.134			
5	.637	7.959	79.092			
6	.589	7.365	86.457			
7	.580	7.247	93.704			
8	.504	6.296	100.000			

Extraction Method: Principal Component Analysis.

The obtained eigen value 3.429 is higher than the random eigen value of 1.0970 generated by the parallel analysis software, confirming the unidimensionality of self efficacysub-scale with 42.858 percent of its total variance explained.

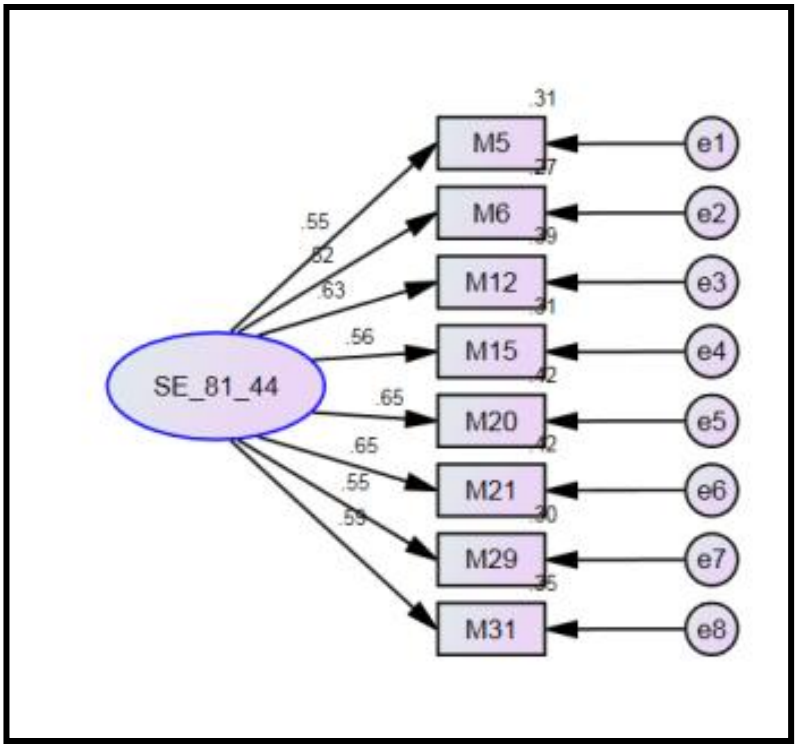


Figure 4.7 **Factor Loadings of Self Efficacy Scale – Original and Parsimonious**

Table 4.38 Goodness of Fit Estimates:

Estimates	CMIN/DF	RMR	GFI	TLI	CFI	RMSEA
Benchmark	<3	<0.08	>0.93	>0.93	>0.93	<0.08
Magnitude	5.611	0.065	0.984	0.96	0.972	0.051

Both the original and revised versions of the MSLQ scale have the same eight items. The obtained fit estimates satisfy their desirable limits, establishing the construct validity of self efficacy scale through the stability of its factor structure.

Table 4.39 Inter-Item Statistics:

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
M5	34.915	51.253	.493	.791
M6	35.281	52.019	.470	.795
M12	34.701	50.738	.552	.782
M15	35.174	51.598	.507	.789
M20	34.873	50.334	.569	.780
M21	34.648	50.624	.564	.781
M29	35.149	51.954	.492	.791
M31	34.906	51.523	.528	.786

Table 4.40 Reliability of Self Efficacy Scale:

Cronbach's α	Guttman's λ 2	McDonald's Ω	Composite Reliability	GLB
0.808	0.809	0.809	0.809	(0.836,1)

Kyriazos et al. (2018) mentioned the suggestion of Kline (1999) that for psychological constructs, the estimate of internal consistency reliability Cronbach alpha could be as low as 0.6. While the true reliability would lie within the confidence interval of 0.836 and 1, the point estimates are close to the acceptable benchmark for the self efficacy scale, indicating its good reliability.

4.2.1.6 Test Anxiety Scale – Psychometrics:

The five items, item 3, 8, 14, 19 and 28 of the test anxiety scale displayed poor psychometrics in the both the versions of MSLQ and hence were not the part of the parsimonious revised version. In this study, the reliability analysis, followed by factor structure and goodness of fit estimates are as follows:

Table 4.41 Reliability of Test Anxiety Scale:

Cronbach's α	Guttman's λ 2	McDonald's Ω	Composite Reliability	GLB
0.616	0.621	0.618	0.619	(0.666,1)

Kyriazos et al. (2018) mentioned the suggestion of Kline (1999) that for psychological constructs, the estimate of internal consistency reliability Cronbach alpha could be as low as 0.6. While the true reliability would lie within the confidence interval of 0.666 and 1, the point estimates are close to the acceptable benchmark for the test anxiety scale, indicating its good reliability.

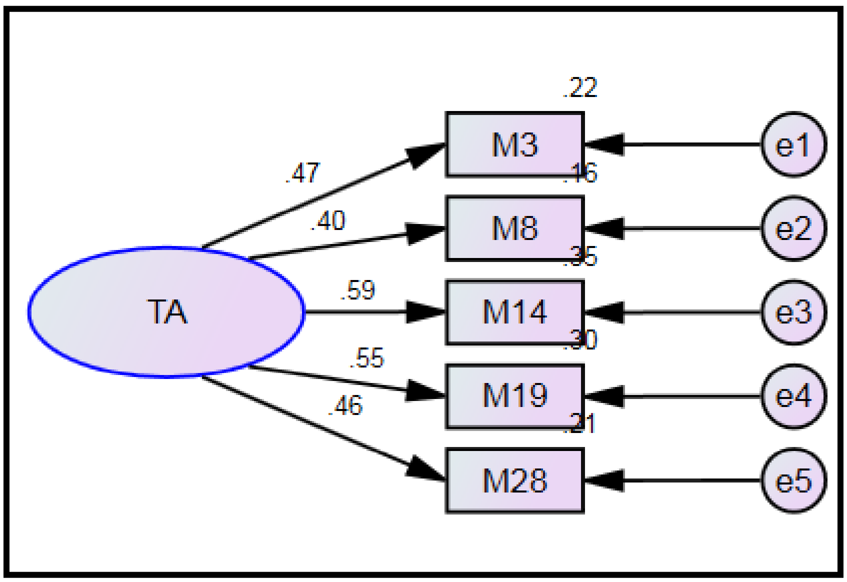


Figure 4.8 **Factor Loadings of Test Anxiety Scale:**

Table 4.42: Goodness of Fit Estimates:

Estimates	CMIN/DF	RMR	GFI	TLI	CFI	RMSEA
Benchmark	<3	<0.08	>0.93	>0.93	>0.93	<0.08
Magnitude	13.872	0.139	0.984	0.852	0.926	0.085

The goodness of fit estimates are acceptable only for GFI. The obtained estimates of the rest of the estimands are below the acceptable benchmark. Owing to this reason, this scale is dropped from the Indian version of MSLQ, though having good reliability estimates.

4.2.1.7 Rehearsal Scale – Psychometrics:

Table 4.43 Descriptive Statistics of the Rehearsal Scale:

Item	Mean	Standard Deviation	Skewness	Kurtosis	Standard Error
39	4.740	1.577	-0.448	-0.355	0.037
46	4.780	1.697	-0.454	-0.645	0.04
59	4.916	1.600	-0.546	-0.338	0.038
72	4.887	1.567	-0.498	-0.364	0.037

Table 4.44 Inter-Item Correlation Matrix:

Correlation Matrix[a]

		M39	M46	M59	M72
Correlation	M39	1.000	.312**	.274**	.300**
	M46	.312**	1.000	.289**	.316**
	M59	.274**	.289**	1.000	.355**
	M72	.300**	.316**	.355**	1.000

a. Determinant = .634

b. ** - Correlation is significant at the **0.01** level (1-tailed)

Table 4.45 KMO and Barlett's Test:

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.717
Bartlett's Test of Sphericity	Approx. Chi-Square	818.341
	df	6
	Sig.	.000

Table 4.46 Total Variance Explained:

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1.923	48.087	48.087	1.923	48.087	48.087
2	.749	18.720	66.807			
3	.687	17.163	83.969			
4	.641	16.031	100.000			

Extraction Method: Principal Component Analysis.

The obtained eigen value 1.923 is higher than the random eigen value of 1.0571 generated by the parallel analysis software, confirming the unidimensionality of Rehearsalsub-scale with 48.087 percent of its total variance explained.

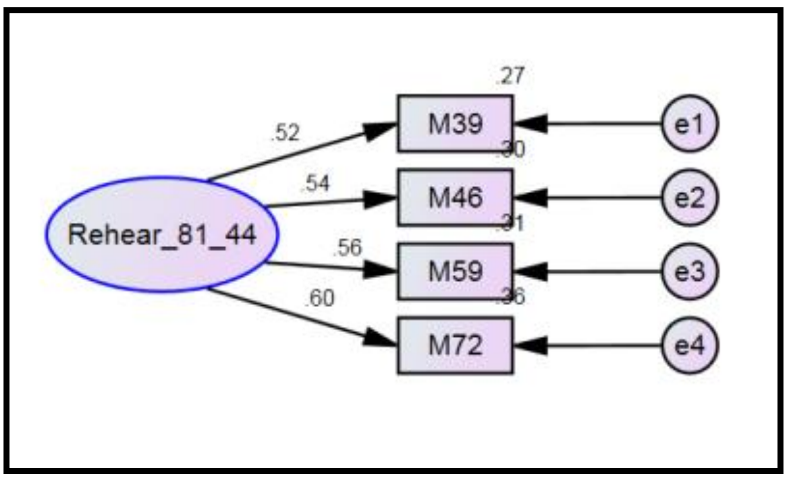


Figure 4.9**Factor Loadings of Rehearsal Scale**

Table 4.47 Goodness of Fit Estimates:

Estimates	**CMIN/DF**	**RMR**	**GFI**	**TLI**	**CFI**	**RMSEA**
Benchmark	<3	<0.08	>0.93	>0.93	>0.93	<0.08
Magnitude	3.526	0.036	0.998	0.981	0.994	0.037

Both the original and revised versions of the MSLQ scale have the same four items. The obtained fit estimates satisfy their desirable limits, establishing the construct validity of Rehearsal scale through the stability of its factor structure.

Table 4.48 Inter-Item Statistics:

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
M39	14.5825	12.925	.400	.584
M46	14.5431	12.148	.416	.574
M59	14.4063	12.657	.416	.573
M72	14.4352	12.544	.445	.552

Table 4.49 Reliability of Rehearsal Scale:

Cronbach's α	Guttman's λ 2	McDonald's Ω	Composite Reliability	GLB
0.639	0.64	0.64	0.641	(0.653,1)

Kyriazos et al. (2018) mentioned the suggestion of Kline (1999) that for psychological constructs, the estimate of internal consistency reliability Cronbach alpha could be as low as 0.6. While the true reliability would lie within the confidence interval of 0.653 and 1, the point estimates are close to the acceptable benchmark for the test anxiety scale, indicating its good reliability.

4.2.1.8 Elaboration Scale – Psychometrics:

Table 4.50 Descriptive Statistics of Elaboration Scale:

Item	Mean	Standard Deviation	Skewness	Kurtosis	Standard Error
53	4.880	1.545	-0.434	-0.398	0.0364
62	4.805	1.508	-0.427	-0.312	0.036
64	4.965	1.536	-0.549	-0.261	0.0362
67	4.877	1.589	-0.482	-0.401	0.03749
69	4.988	1.503	-0.588	-0.123	0.035
81	4.900	1.572	-0.542	-0.247	0.03707

Table 4.51 Inter-Item Correlation Matrix:

Correlation Matrix[a]

		M53	M62	M64	M67	M69	M81
Correlation	M53	1.000	.365**	.311**	.350**	.306**	.368**
	M62	.365**	1.000	.424**	.325**	.402**	.388**
	M64	.311**	.424**	1.000	.394**	.365**	.352**
	M67	.350**	.325**	.394**	1.000	.495**	.330**
	M69	.306**	.402**	.365**	.495**	1.000	.362**
	M81	.368**	.388**	.352**	.330**	.362**	1.000

a. Determinant = .264

b. ** - Correlation is significant at the **0.01** level (1-tailed)

Table 4.52 KMO and Barlett's Test:

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.829
Bartlett's Test of Sphericity	Approx. Chi-Square	2391.041
	df	15
	Sig.	.000

Table 4.53 Total Variance Explained:

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.849	47.476	47.476	2.849	47.476	47.476
2	.770	12.827	60.303			
3	.695	11.580	71.882			

4	.632	10.536	82.419			
5	.591	9.852	92.271			
6	.464	7.729	100.000			

Extraction Method: Principal Component Analysis.

The obtained Eigen value 2.849 is higher than the random eigen value of 1.0789 generated by the parallel analysis software, confirming the unidimensionality of Elaborationsub-scale with 47.476 percent of its total variance explained.

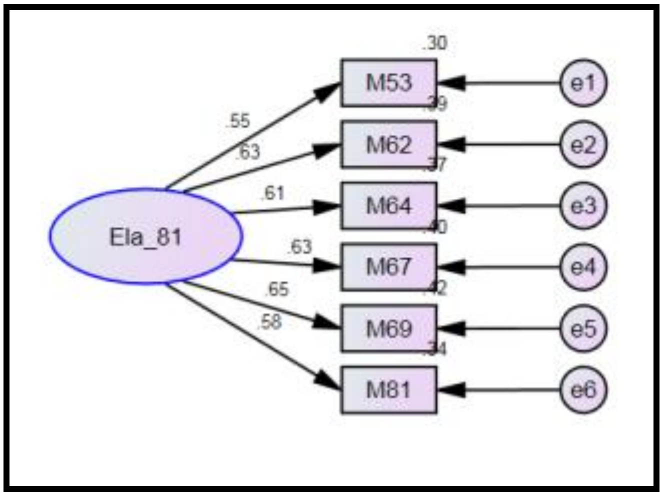


Figure 4.10 **Factor Loadings of Elaboration Scale**

Table 4.54 Goodness of Fit Estimates:

Estimates	CMIN/ DF	RMR	GFI	TLI	CFI	RMSEA	AIC	BIC
Benchmark	<3	<0.08	>0.93	>0.93	>0.93	<0.08	-	-
Magnitude	12.522	0.08	0.98	0.927	0.956	0.08	136.695	202.635

The revised version of MSLQ (2018) dropped the item 67 of elaboration scale. Rest of the five items 53, 62, 64, 69 and 81 collectively provided explanation to 49.206 % variance forming one factor. Their factor structure is shown below:

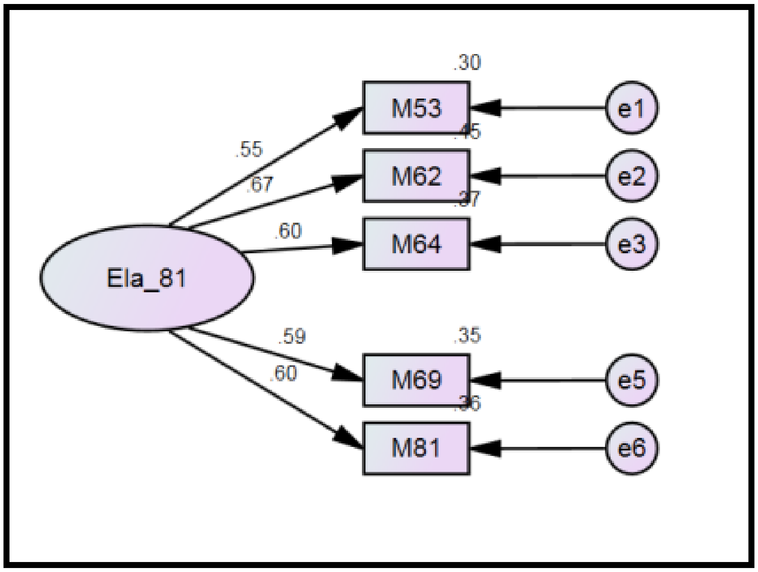


Figure 4.11 **Factor Loadings of Parsimonious Elaboration Scale**

Table 4.55 Goodness of Fit Estimates of Parsimonious Elaboration Scale:

Estimates	**CMIN/DF**	**RMR**	**GFI**	**TLI**	**CFI**	**RMSEA**	**AIC**	**BIC**
Benchmark	<3	<0.08	>0.93	>0.93	>0.93	<0.08	136.695	202.635
Magnitude	2.578	0.034	0.997	0.991	0.995	0.03	32.891	87.840

On comparison of the AIC and BIC estimates of theElaboration scale in original and revised versions of MSLQ,to select the better model, these estimates were found to be lowered for the later model and hence its items were retained in this study.

Table 4.56 Inter-Item Statistics:

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
M53	19.6576	20.094	.461	.712
M62	19.7332	19.266	.554	.677
M64	19.5725	19.689	.501	.697
M69	19.5503	19.976	.494	.699
M81	19.6387	19.364	.509	.694

Table 4.57 Reliability of Elaboration Scale:

Cronbach's α	Guttman's λ 2	McDonald's Ω	Composite Reliability	GLB
0.714	0.742	0.742	0.74	(0.756,1)

Kyriazos et al. (2018) mentioned the suggestion of Kline (1999) that for psychological constructs, the estimate of internal consistency reliability Cronbach alpha could be as low as 0.6. While the true reliability would lie within the confidence interval of 0.756 and 1, the point estimates are close to the acceptable benchmark for the test anxiety scale, indicating its very good reliability.

4.2.1.9 Organization Scale – Psychometrics:

Since the revised version of MSLQ(2018) study included only two items, item 42 and 63 in its study, negating the recommendation of Tabachnick and Fidell (2011) to have at least three items per factor, the present study considered all the four items, item 32, 42, 49 and 63 for this study for testing the psychometrics of organization scale.

Table 4.58 Descriptive Statistics of Organization Scale:

Item	Mean	Standard Deviation	Skewness	Kurtosis	Standard Error
32	4.973	1.57	-0.558	-0.284	0.037
42	5.036	1.558	-0.539	-0.337	0.036
49	4.861	1.67	-0.568	-0.408	0.039
63	5.019	1.52	-0.512	-0.356	0.036

Table 4.59 Inter-Item Correlation Matrix:

Correlation Matrix[a]

		M32	M42	M49	M63
Correlation	M32	1.000	.362**	.354**	.321**
	M42	.362**	1.000	.326**	.400**

M49	.354**	.326**	1.000	.366**
M63	.321**	.400**	.366**	1.000

a. Determinant = .549

b. ** - Correlation is significant at the **0.01** level (1-tailed)

Table 4.60 KMO and Barlett's Test:

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.736
Bartlett's Test of Sphericity	Approx. Chi-Square	1076.082
	df	6
	Sig.	.000

Table 4.61 Total Variance Explained:

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.065	51.623	51.623	2.065	51.623	51.623
2	.689	17.233	68.856			
3	.669	16.718	85.574			
4	.577	14.426	100.000			

Extraction Method: Principal Component Analysis.

The obtained eigen value 2.065 is higher than the random eigen value of 1.0521 generated by the parallel analysis software, confirming the unidimensionality of Organizationsub-scale with 51.623 percent of its total variance explained.

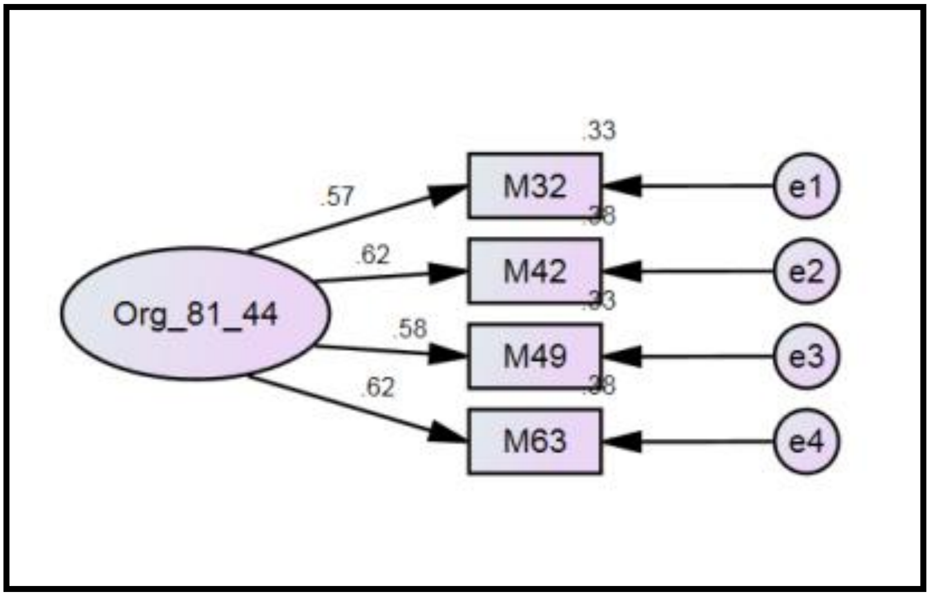


Figure 4.12 **Factor Loadings of Organization Scale – Original and Revised**

Table 4.62 Goodness of Fit Estimates:

Estimates	**CMIN/DF**	**RMR**	**GFI**	**TLI**	**CFI**	**RMSEA**
Benchmark	<3	<0.08	>0.93	>0.93	>0.93	<0.08
Magnitude	6.656	0.044	0.996	0.968	0.989	0.056

Ignoring CMIN/DF estimates owing to its sensitivity to sample size, rest of the goodness of fit estimates are in favor of indicating the construct validity of Organization scale through the intactness of its factor structure.

Table 4.63 Inter-Item Statistics:

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
M32	14.9166	13.036	.456	.630
M42	14.8538	12.869	.481	.615
M49	15.0289	12.452	.461	.629
M63	14.8705	13.012	.482	.614

Table 4.64 Reliability of Organization Scale:

Cronbach's α	Guttman's λ 2	McDonald's Ω	Composite Reliability	GLB
0.687	0.687	0.687	0.69	(0.717,1)

Kyriazos et al. (2018) mentioned the suggestion of Kline (1999) that for psychological constructs, the estimate of internal consistency reliability Cronbach alpha could be as low as 0.6. While the true reliability would lie within the confidence interval of 0.717 and 1, the point estimates are close to the acceptable benchmark for the organization scale, indicating its good reliability.

4.2.1.10 Critical Thinking Scale – Psychometrics:

Table 4.65 Descriptive Statistics of Critical Thinking Scale:

Item	**Mean**	**Standard Deviation**	**Skewness**	**Kurtosis**	**Standard Error**
38	4.662	1.534	-0.363	-0.318	0.036
47	4.759	1.484	-0.447	-0.218	0.350
51	4.842	1.510	-0.416	-0.356	0.356
66	4.792	1.532	-0.436	-0.34	0.361

71	4.877	1.441	-0.508	-0.054	0.339

Table 4.66 Inter-Item Correlation:

Correlation Matrix[a]

		M38	M47	M51	M66	M71
Correlation	M38	1.000	.340**	.311**	.335**	.322**
	M47	.340**	1.000	.382**	.329**	.374**
	M51	.311**	.382**	1.000	.378**	.404**
	M66	.335**	.329**	.378**	1.000	.388**
	M71	.322**	.374**	.404**	.388**	1.000

a. Determinant = .410

b. ** - Correlation is significant at the **0.01** level (1-tailed)

Table 4.67 KMO and Barlett's Test:

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.805
Bartlett's Test of Sphericity	Approx. Chi-Square	1599.695
	df	10
	Sig.	.000

Table 4.68 Total Variance Explained:

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.427	48.545	48.545	2.427	48.545	48.545
2	.712	14.247	62.793			
3	.672	13.431	76.223			
4	.596	11.914	88.137			
5	.593	11.863	100.000			

Extraction Method: Principal Component Analysis.

The obtained Eigen value 2.427 is higher than the random eigen value of 1.0665 generated by the parallel analysis software, confirming the unidimensionality of Crtitical thinkingsub-scale with 48.545 percent of its total variance explained.

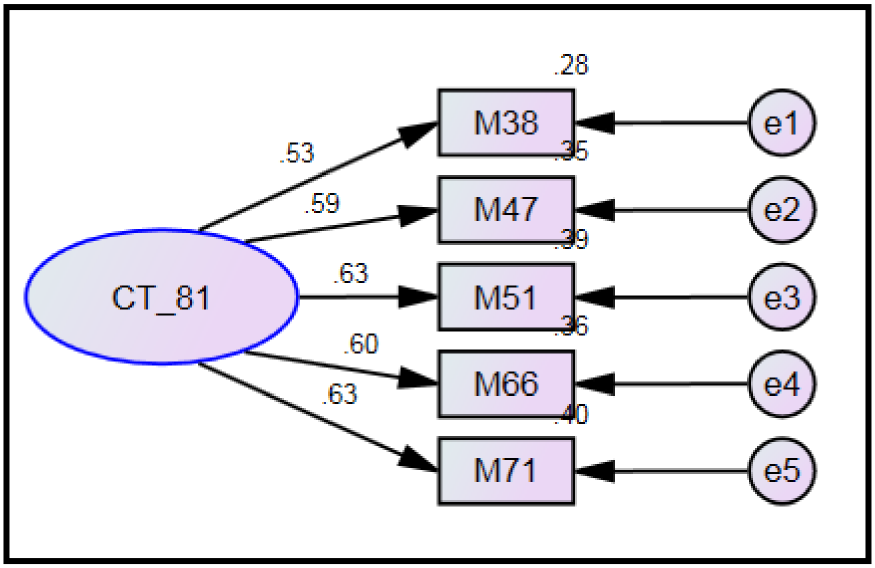


Figure 4.13 **Factor Loadings of Critical Thinking Scale:**

Table 4.69 Goodness of Fit Estimates:

Estimates	CMIN/DF	RMR	GFI	TLI	CFI	RMSEA	AIC	BIC
Benchmark	<3	<0.08	>0.93	>0.93	>0.93	<0.08	-	-
Magnitude	2.109	0.029	0.998	0.993	0.997	0.025	30.545	85.495

The item 38 of the critical thinking scale in the revised version of MSLQ is dropped. The remaining four items 47, 51, 66 and 71 from the original scale (1991) collectively explained 53.201 % variance of this unidimensional variable. The factor structure is shown below:

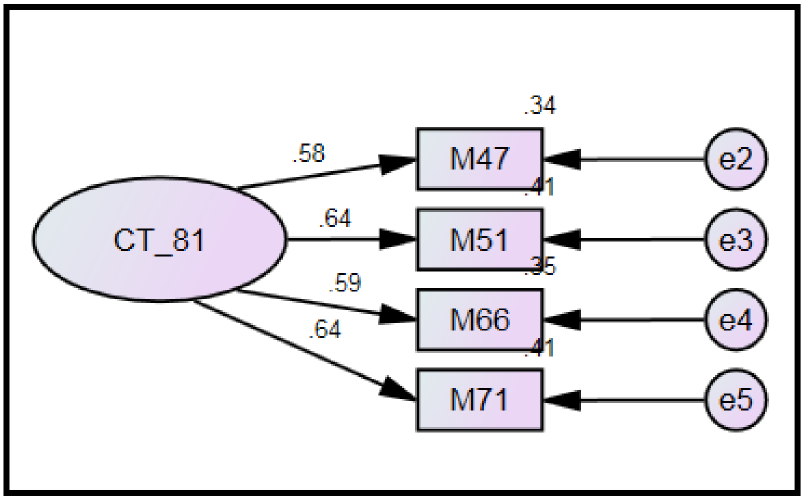


Figure 4.14 **Factor Loadings of Parsimonious Critical Thinking Scale**

Table 4.70 Goodness of Fit Estimates of the Parsimonious Critical Thinking Scale:

Estimates	**CMIN/DF**	**RMR**	**GFI**	**TLI**	**CFI**	**RMSEA**	**AIC**	**BIC**
Benchmark	<3	<0.08	>0.93	>0.93	>0.93	<0.08	30.545	85.495
Magnitude	0.959	0.015	0.999	1.000	1.000	0.000	17.918	61.878

The estimates of AIC and BIC for the parsimonious revised version of MSLQ (2018) were lower than the same estimates of original model (1991). As a result, the items of the revised model are retained in this study.

Table 4.71 Inter-Item Statistics:

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
M47	14.5120	11.933	.469	.657
M51	14.4286	11.443	.511	.631
M66	14.4792	11.633	.475	.654
M71	14.3941	11.794	.512	.631

Table 4.72 Reliability of the Critical Thinking Scale

Cronbach's α	Guttman's λ 2	McDonald's Ω	Composite Reliability	GLB
0.706	0.706	0.707	0.765	(0.716,1)

Kyriazos et al. (2018) mentioned the suggestion of Kline (1999) that for psychological constructs, the estimate of internal consistency reliability Cronbach alpha could be as low as 0.6. While the true reliability would lie within the confidence interval of 0.716 and 1, the point estimates are close to the acceptable benchmark for the critical thinking scale, indicating its good reliability.

4.2.1.11 Metacognitve Self Regulation Scale – Psychometrics:

Table 4.73 Descriptive Statistics of Metacognitive Self Regulation Scale:

Item	Mean	Standard Deviation	Skewness	Kurtosis	Standard Error
33	3.562	1.877	0.310	-0.955	0.044
36	4.853	1.590	-0.515	-0.349	0.037
41	4.898	1.560	-0.506	-0.275	0.0367
44	4.946	1.549	-0.561	-0.166	0.0365
54	4.68	1.528	-0.431	-0.276	0.036
55	4.843	1.561	-0.495	-0.341	0.0368
56	4.794	1.556	-0.546	-0.167	0.036705
57	3.714	1.743	0.264	-0.777	0.041
61	4.765	1.505	-0.433	-0.226	0.035
76	4.966	1.523	-0.606	-0.090	0.0359
78	4.829	1.542	-0.492	-0.298	0.0363
79	4.733	1.618	-0.537	-0.282	0.0381

The revised parsimonious version of MSLQ considered only six of the original version of MSLQ (1991) items, that is, item 41, 44, 54, 55, 56, 76 and 78. Collectively, they explained 42.460 % variance in metacognitive self regulation variable as a single factor.

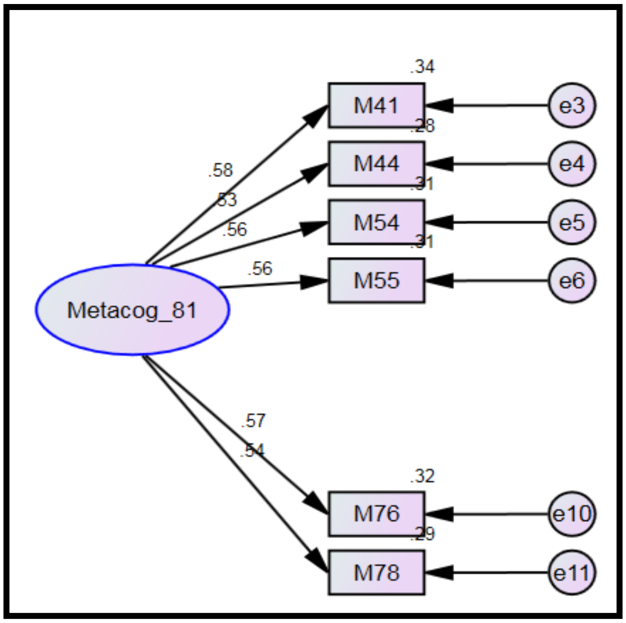


Figure.4.15 **Factor Loadings of the Parsimonious Metacognitive Self Regulation Scale:**

Table 4.74 Goodness of Fit Estimates:

Estimates	CMIN/DF	RMR	GFI	TLI	CFI	RMSEA
Benchmark	<3	<0.08	>0.93	>0.93	>0.93	<0.08
Magnitude	10.172	0.081	0.983	0.92	0.952	0.071

The revised parsimonious version of metacognitive self regulation sub scale with its six items showed moderate fit in the Indian context and was retained.

Table 4.75 Inter-Item Statistics:

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
M41	24.2657	26.234	.486	.684
M44	24.2173	27.008	.437	.699
M54	24.4836	26.800	.461	.692

M55	24.3207	26.511	.465	.690
M76	24.1979	26.650	.475	.688
M78	24.3346	26.851	.451	.695

Table 4.76 Reliability of Metacognitive Self Regulation Scale:

Cronbach's α	Guttman's λ 2	McDonald's Ω	Composite Reliability	GLB
0.729	0.73	0.728	0.729	(0.77,1)

Kyriazos et al. (2018) mentioned the suggestion of Kline (1999) that for psychological constructs, the estimate of internal consistency reliability Cronbach alpha could be as low as 0.6. While the true reliability would lie within the confidence interval of 0.77 and 1, the point estimates are close to the acceptable benchmark for the metacognitive self regulation scale, indicating its good reliability.

4.2.1.12 Time and Study Environment Scale – Psychometrics:

Table 4.77 Descriptive Statistics of Time and Study Environment Scale:

Item	Mean	Standard Deviation	Skewness	Kurtosis	Standard Error
35	5.118	1.578	-0.638	-0.237	0.0372
43	4.878	1.574	-0.509	-0.333	0.0371
52	3.290	1.669	0.482	-0.510	0.0393
65	4.684	1.693	-0.484	-0.507	0.03992
70	4.663	1.705	-0.433	-0.640	0.040
73	5.120	1.631	-0.634	-0.300	0.0384
77	3.446	1.695	0.439	-0.586	0.03998
80	3.521	1.803	0.412	-0.776	0.042

The four items 35, 43, 65 and 70 of the revised parsimonious version of Time and Study Environment Scale of MSLQ (2018) collectively form a single factor and explain 50.328 % variance in it.

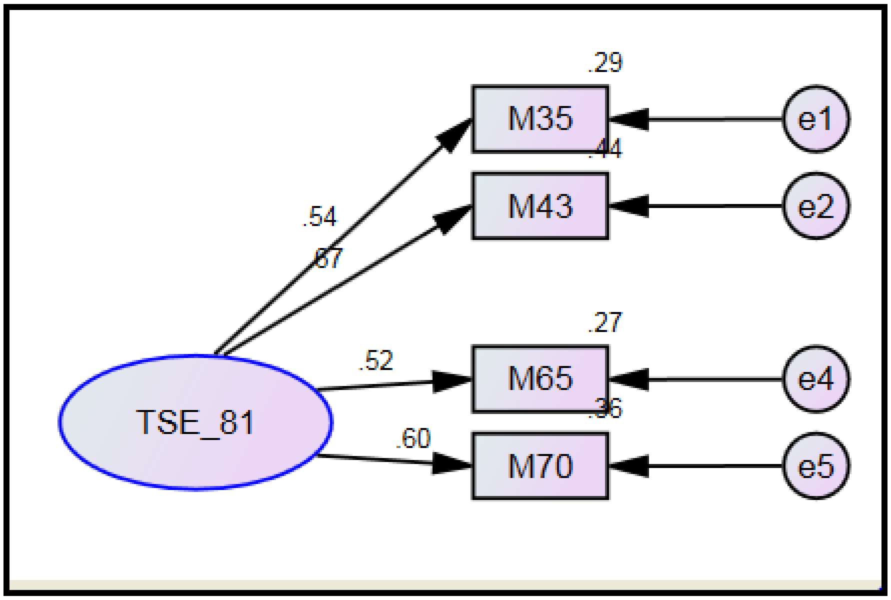


Figure4.16 **Factor Loadings of the Parsimonious Time and Study Environment Scale:**

Table 4.78 Goodness of Fit Estimates of Parsimonious Time and Study Environment Scale:

Estimates	**CMIN/DF**	**RMR**	**GFI**	**TLI**	**CFI**	**RMSE"**
Benchmark	<3	<0.08	>0.93	>0.93	>0.93	<0.08
Magnitude	3.694	0.036	0.998	0.984	0.995	0.039

There is enough evidence to show that the variable time and study environment sub scale has stable factor structure since barring CMIN/DF estimate, rest of the goodness of fit estimates have values satisfying their respective benchmark values.

Table 4.79 Inter-Item Statistics:

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
M35	14.226	14.024	.427	.617
M43	14.466	13.331	.500	.570
M65	14.660	13.522	.416	.626

M70	14.681	12.997	.460	.595

Table 4.80 Reliability of Time and Study Environment Scale:

Cronbach's α	Guttman's λ 2	McDonald's Ω	Composite Reliability	GLB
0.669	0.67	0.672	0.674	(0.695,1)

Kyriazos et al. (2018) mentioned the suggestion of Kline (1999) that for psychological constructs, the estimate of internal consistency reliability Cronbach alpha could be as low as 0.6. While the true reliability would lie within the confidence interval of 0.695 and 1, the point estimates are close to the acceptable benchmark for the time and study environment scale, indicating its good reliability.

4.2.1.13 Effort Regulation and Peer Learning Scale – Psychometrics:

The obtained internal consistency reliability estimate, the Cronbach alpha, for the scale effort regulation with its four items, that is, item 37, 48, 60 and 74, is very dismal at 0.218, leading to its elimination from the present study. The sub scale peerl learning is also dropped from this study due to the same reason with its three items 34, 45 and 50 collectively displaying a below the acceptable estimate of internal consistency Cronbach's alpha at 0.583.

4.2.1.14 Help Seeking Scale – Psychometrics:

The original scale of MSLQ (1991) had four items, that is, item 40, 58, 68 and 75 under help seeking sub-scale. It was dropped in the revised parsimonious version of MSLQ study (2018).

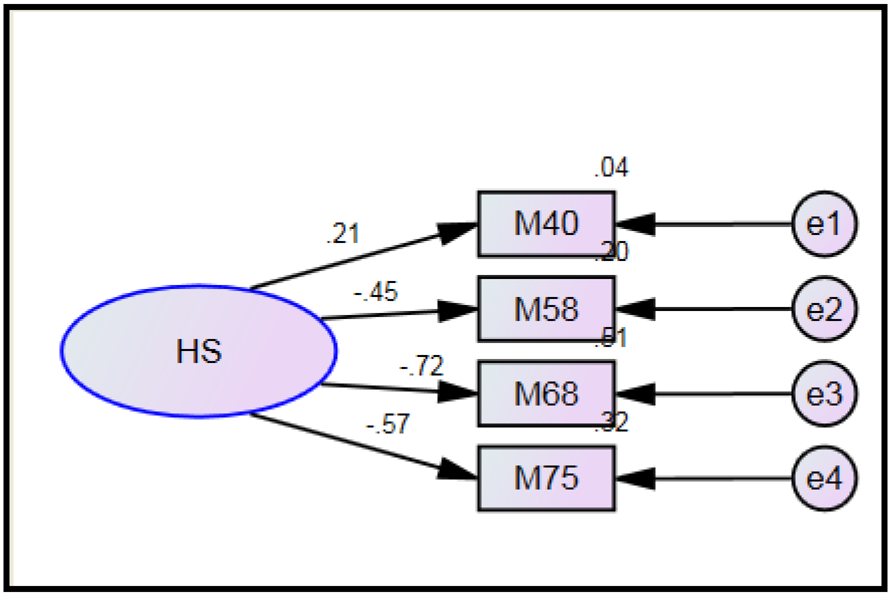


Figure 4.17**Factor Loadings of Help-seeking Scale:**

Table 4.81 Goodness of Fit Estimates of Help Seeking Scale:

Estimates	**CMIN/DF**	**RMR**	**GFI**	**TLI**	**CFI**	**RMSEA**
Benchmark	<3	<0.08	>0.93	>0.93	>0.93	<0.08
Magnitude	5.286	0.048	0.997	0.959	0.986	0.049

There is enough evidence to show that the variable help seeking sub scale has stable factor structure since barring CMIN/DF estimate, rest of the goodness of fit estimates have values satisfying their respective benchmark values.

Table 4.82 Reliability of Help Seeking Scale:

Cronbach's α	Guttman's λ 2	McDonald's Ω	Composite Reliability	GLB
0.295	0.417	0.566	N/A due to negative factor loading	(0.607,1)

Except, the greatest lower bound reliability, rest of the reliability estimates, do not indicate consistency in measurement capability of the help seeking scale. Three of its four items have negative factor loadings in its factor structure indicating that these items measure a variable contrary to the essence of help seeking. Owing to the obtaining of these psychometric evidences, the scale is eliminated from this study.

Table 4.83 Snapshot of the Status of the Sub scales of MSLQ Validated in 1991, 2018 and 2019:

S.No.	Sub Scale	Original MSLQ 81 Items Pintrich et al. (1991)	Parsimonious MSLQ - R 44 Items Jackson (2018)	Present Indian Version of MSLQ 56 Items (2019)	Remark
1.	Intrinsic GO	1, 16, 22, 24	1, 16, 22, 24	1, 16, 22, 24 (4)	No change
2.	Extrinsic GO	7, 11, 13, 30	Eliminated	7, 11, 13, 30 (4)	Original scale Retained
3.	Task Value	4, 10, 17, 23, 26, 27	4, 17, 23, 26, 27	4, 17, 23, 26, 27 (5)	Parsimonious scale Retained
4.	Control of LB	2, 9, 18, 25	2, 9, 18, 25	2, 9, 18, 25 (4)	No change
5.	Self Efficacy	5, 6, 12, 15, 20, 21, 29, 31	5, 6, 12, 15, 20, 21, 29, 31	5, 6, 12, 15, 20, 21, 29, 31 (8)	No change
6.	Test Anxiety	3, 8, 14, 19, 28	Eliminated	Eliminated	Eliminated
7.	Rehearsal	39, 46, 59, 72	39, 46, 59, 72	39, 46, 59, 72 (4)	No change
8.	Elaboration	53, 62, 64, 67, 69, 81	53, 62, 64, 69, 81	53, 62, 64, 69, 81 (5)	Parsimonious scale Retained
9.	Organization	32, 42, 49, 63	42, 63	32, 42, 49, 63 (4)	Original scale Retained
10.	Critical Thinking	38, 47, 51, 66, 71	47, 51, 66, 71	47, 51, 66, 71 (4)	Parsimonious scale Retained
11.	Meta cognitive	33R, 36, 41, 44,	41, 44, 54, 55, 76, 78	41, 44, 54, 55, 76, 78	Parsimonious

	self regulation	54, 55, 56, 57R, 61, 76, 78, 79		(6)	scale Retained
12.	Time and Study	35, 43, 52R, 65, 70, 73, 77R, 80R	35, 43, 65,70	35, 43, 65,70 (4)	Parsimonious scale Retained
13.	Effort Regulation	37R, 48, 60R, 74	48,74	Eliminated	Eliminated
14.	Peer Learning	34, 45, 50	Eliminated	Eliminated	Eliminated
15.	Help Seeking	40R, 58, 68, 75	Eliminated	Eliminated	Eliminated

Conclusion: Four scales, help seeking, test anxiety, effort regulation and peer learning are removed from this study as they displayed poor psychometrics with weak items (Crede and Phillips, 2011; Rotgans and Schmidt, 2010).Remaining scales either fully retained or partially retained their factor structure intactness in this adaptation study of MSLQ(Chechi, Bhalla and Chakraborty, 2019) in the Indian context. Further studies can extend the validation study with larger sample size and on divergent population and testing the measurement invariance of these scales with respect to gender and other vital demographic variables as guided by literature review of self regulated learning. The initial validation of this vital instrument can now allow the usage of this scale by researchers in India to administer it on their subjects with statistically backed evidence of its validity.

4.2.1.15 Application of Network Psychometrics on the Chosen Sub-scales of MSLQ:

In the present study, the cognitive component of self regulated learning was measured using the critical thinking and organization sub scales of MSLQ. The behavioral component was measured using its time and study environment scale. Two more sub scales, self efficacy and goal orientation, were used to measure the motivational belief sub component of the motivation component of self regulated learning. The sub-scales self efficacy and goal orientation belong to the Motivation portion of MSLQ scale and the sub-scales critical thinking, organization and time and study environment are part of learning strategies portion of the MSLQ scale. The validation of this aspect of the scale using Network Analysis in R along with the codes and results is presented below:

```
>library(haven) # Import data file
>MSLQ_SRL_Variables_Data <- read_sav("D:/New Research/NP/MSLQ/MSLQ_SRL_Variables_Data.sav")
>View(MSLQ_SRL_Variables_Data)
> ega.MSLQ<-EGA(MSLQ_SRL_Variables_Data, plot.EGA = TRUE)

>install.packages("EGAnet")
>library(EGAnet)
```

> ega.MSLQ<-EGA(MSLQ_SRL_Variables_Data, plot.EGA = TRUE)

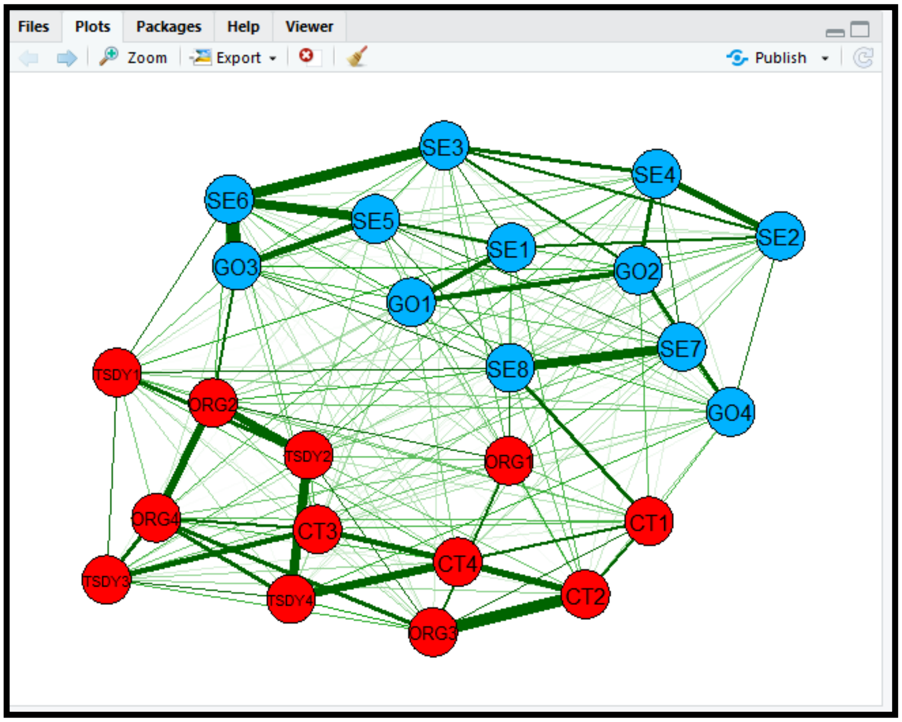


Figure 4.18 **Explored Network Structure of the Items with their respective sub-scales of Motivation and Learning Strategies Questionnaire (MSLQ):**

> summary(ega.MSLQ)
EGA Results:

Number of Dimensions:
[1] 2

Items per Dimension:
items dimension
CT1 CT1 1
CT2 CT2 1
CT3 CT3 1
CT4 CT4 1
ORG1 ORG1 1
ORG2 ORG2 1
ORG3 ORG3 1
ORG4 ORG4 1
TSDY1 TSDY1 1
TSDY2 TSDY2 1

```
TSDY3 TSDY3        1
TSDY4 TSDY4        1
GO1    GO1       2
GO2    GO2       2
GO3    GO3       2
GO4    GO4       2
SE1    SE1       2
SE2    SE2       2
SE3    SE3       2
SE4    SE4       2
SE5    SE5       2
SE6    SE6       2
SE7    SE7       2
SE8    SE8       2  # Factor 1 – Learning Strategies; Factor 2 – Motivation
```

Interpretation: The exploratory graph analysis reveal the presence of sub-scales critical thinking, organization and time and study environment under learning strategies scale and self efficacy and goal orientation under motivation scale.

```
> install.packages("lavaan")
> library(lavaan)
> cfa.MSLQ<- CFA(ega.obj = ega.MSLQ, estimator = 'WLSMV', plot.CFA = TRUE, data = MSLQ_SRL_Variables_Data)
[1] CT1   CT2   CT3   CT4   ORG1  ORG2  ORG3  ORG4  TSDY1 TSDY2 TSDY3 TSDY4
24 Levels: CT1 CT2 CT3 CT4 GO1 GO2 GO3 GO4 ORG1 ORG2 ORG3 ORG4 SE1 SE2 ... TSDY4
[1] GO1 GO2 GO3 GO4 SE1 SE2 SE3 SE4 SE5 SE6 SE7 SE8
24 Levels: CT1 CT2 CT3 CT4 GO1 GO2 GO3 GO4 ORG1 ORG2 ORG3 ORG4 SE1 SE2 ... TSDY4
```

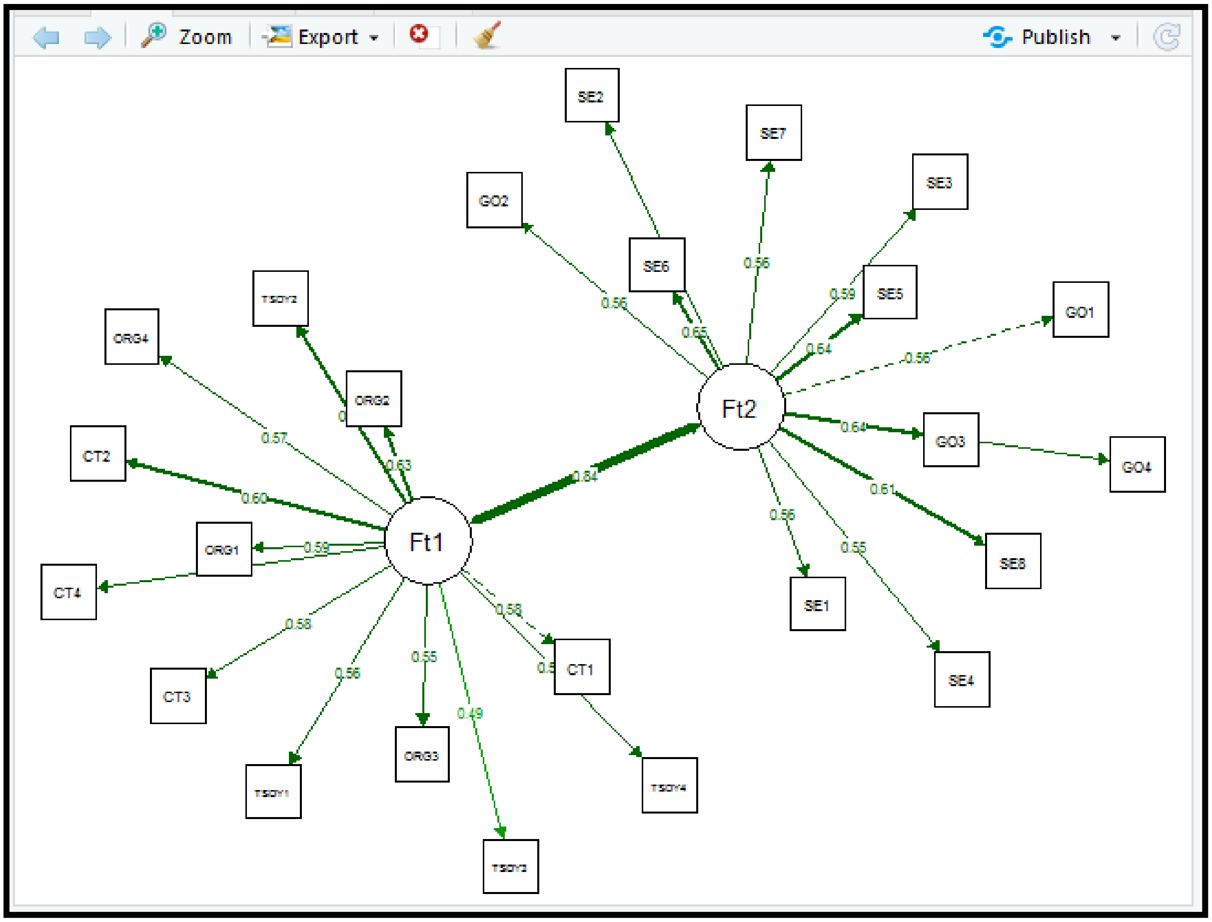


Figure 4.19 **Factor Loadings of the MSLQ Items**

```
> lavaan::fitMeasures(cfa.MSLQ$fit, fit.measures = "all")
npar                    fmin
49.000                  0.100
chisq                   df
359.987                 251.000
pvalue             chisq.scaled
0.000              621.610
df.scaled              pvalue.scaled
251.000                0.000
chisq.scaling.factor            baseline.chisq
0.579                 35861.596
baseline.df             baseline.pvalue
276.000                 0.000
baseline.chisq.scaled          baseline.df.scaled
35861.596                276.000
baseline.pvalue.scaled baseline.chisq.scaling.factor
0.000                  1.000
cfi                    tli
```

0.997 0.997
nnfi rfi
0.997 0.989
nfi pnfi
0.990 0.900
ifi rni
0.997 0.997
cfi.scaled tli.scaled
0.990 0.989
cfi.robust tli.robust
0.994 0.993
nnfi.scaled nnfi.robust
0.989 0.993
rfi.scaled nfi.scaled
0.981 0.983
ifi.scaled rni.scaled
0.990 0.990
rni.robust rmsea
0.994 0.016
rmsea.ci.lower rmsea.ci.upper
0.012 0.019
rmsea.pvalue rmsea.scaled
1.000 0.029
rmsea.ci.lower.scaled rmsea.ci.upper.scaled
0.025 0.032
rmsea.pvalue.scaled rmsea.robust
1.000 0.022
rmsea.ci.lower.robust rmsea.ci.upper.robust
0.020 0.024
rmsea.pvalue.robust rmr
NA 0.073
rmr_nomean srmr
0.073 0.030
srmr_bentler srmr_bentler_nomean
0.030 0.030
crmr crmr_nomean
0.031 0.031
srmr_mplus srmr_mplus_nomean
0.030 0.030
cn_05 cn_01
1444.224 1529.575
gfi agfi
0.994 0.993

pgfi mfi
0.832 0.970
ecvi
0.255

Interpretation: The robust estimands of confirmatory factor analysis under network analysis found using the WLSMV estimator all indicate excellent fit of the five sub-scales within the two scales of MSLQ. The robust CFI is 0.994 (>0.95), the robust TLI is 0.993 (> 0.95) , the robust RMSEA is 0.022 (<0.05) and the bentler SRMR is 0.03 (<0.08).

> View(ega.MSLQ$dim.variables)

	items	dimension
CT1	CT1	1
CT2	CT2	1
CT3	CT3	1
CT4	CT4	1
ORG1	ORG1	1
ORG2	ORG2	1
ORG3	ORG3	1
ORG4	ORG4	1
TSDY1	TSDY1	1
TSDY2	TSDY2	1
TSDY3	TSDY3	1

Filter

	items	dimension
TSDY4	TSDY4	1
GO1	GO1	2
GO2	GO2	2
GO3	GO3	2
GO4	GO4	2
SE1	SE1	2
SE2	SE2	2
SE3	SE3	2
SE4	SE4	2
SE5	SE5	2
SE6	SE6	2
SE7	SE7	2
SE8	SE8	2

> net.loads(ega.MSLQ$network, ega.MSLQ$wc)$std
1 2
CT1 0.189 0.081
CT2 0.221 0.070

CT3 0.199 0.068
CT4 0.228 0.059
ORG1 0.151 0.125
ORG2 0.178 0.125
ORG3 0.250 0.014
ORG4 0.250 0.031
GO1 0.075 0.188
GO2 0.051 0.216
GO3 0.083 0.231
GO4 0.102 0.137
TSDY1 0.143 0.115
TSDY2 0.233 0.078
TSDY3 0.202 0.025
TSDY4 0.213 0.040
SE1 0.083 0.174
SE2 0.030 0.196
SE3 0.040 0.238
SE4 0.045 0.211
SE5 0.039 0.266
SE6 0.085 0.243
SE7 0.073 0.182
SE8 0.127 0.172

In order to conduct inferential analysis on the exploratory graph analysis based factor extraction, the package bootnet is installed in R.

```
> install.packages("bootnet")
> library(bootnet)
> Network <- estimateNetwork(MSLQ_SRL_Variables_Data,default = "EBICglasso")
> install.packages("qgraph")

> library(qgraph)
> plot(Network, layout = "spring",labels = TRUE)
```

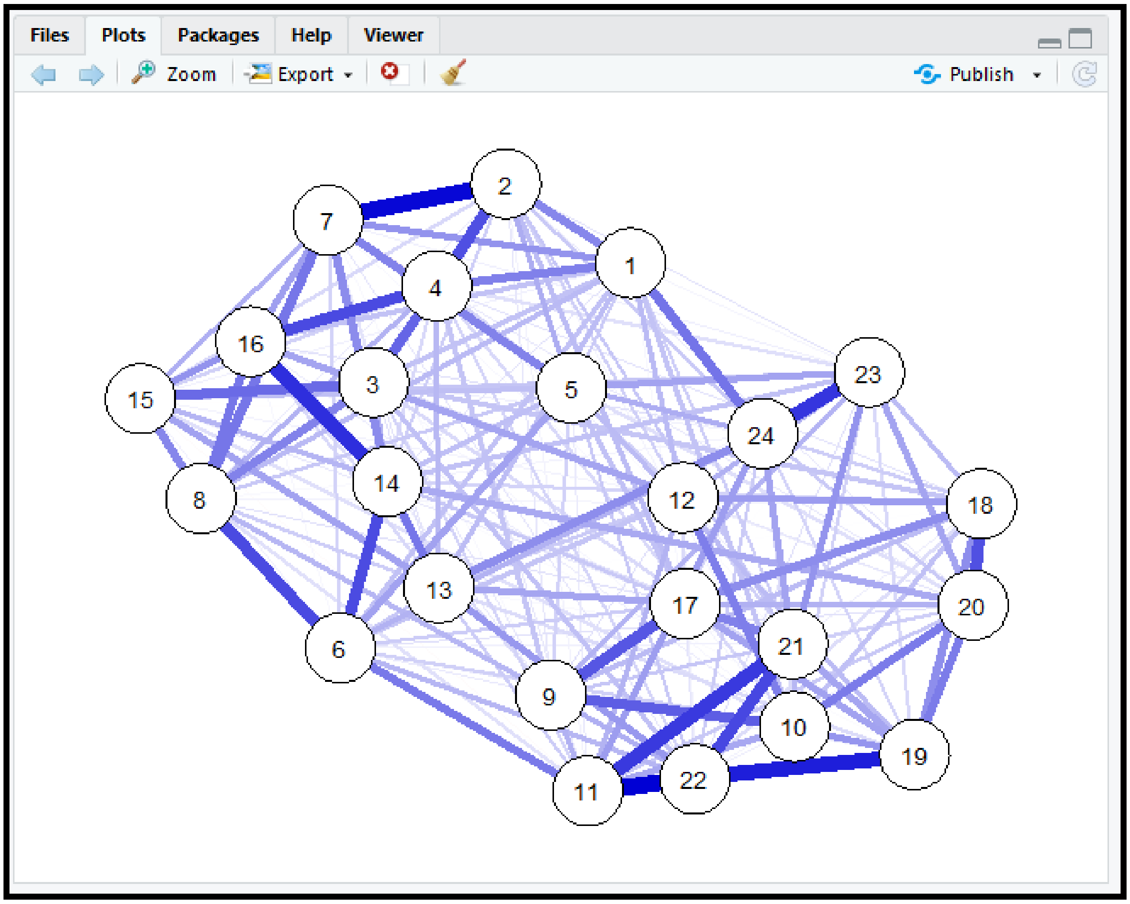


Figure 4.20 **The Network Structure of the items of MSLQ sub-scales**

> centralityPlot(Network)

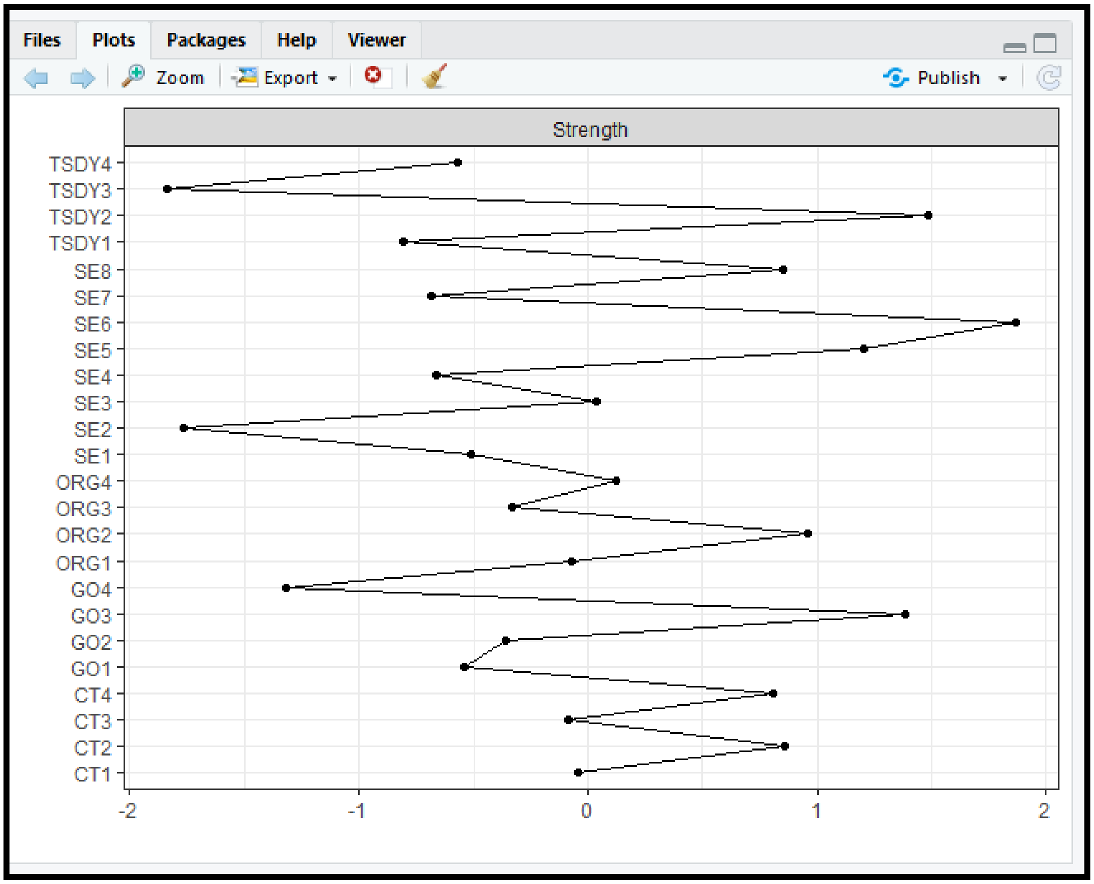


Figure 4.21 **Strength Centrality Index**

Interpretation: The above figure shows that among all the items of the five sub-scales, the item 3 of time and study environment sub-scale has the lowest edge strength and the item 6 fo self efficacy sub-scale has the highest edge strength.

```
> boot1 <- bootnet(Network, nBoots = 50,nCores = 8)
> plot(boot1, labels = FALSE, order = "sample")
```

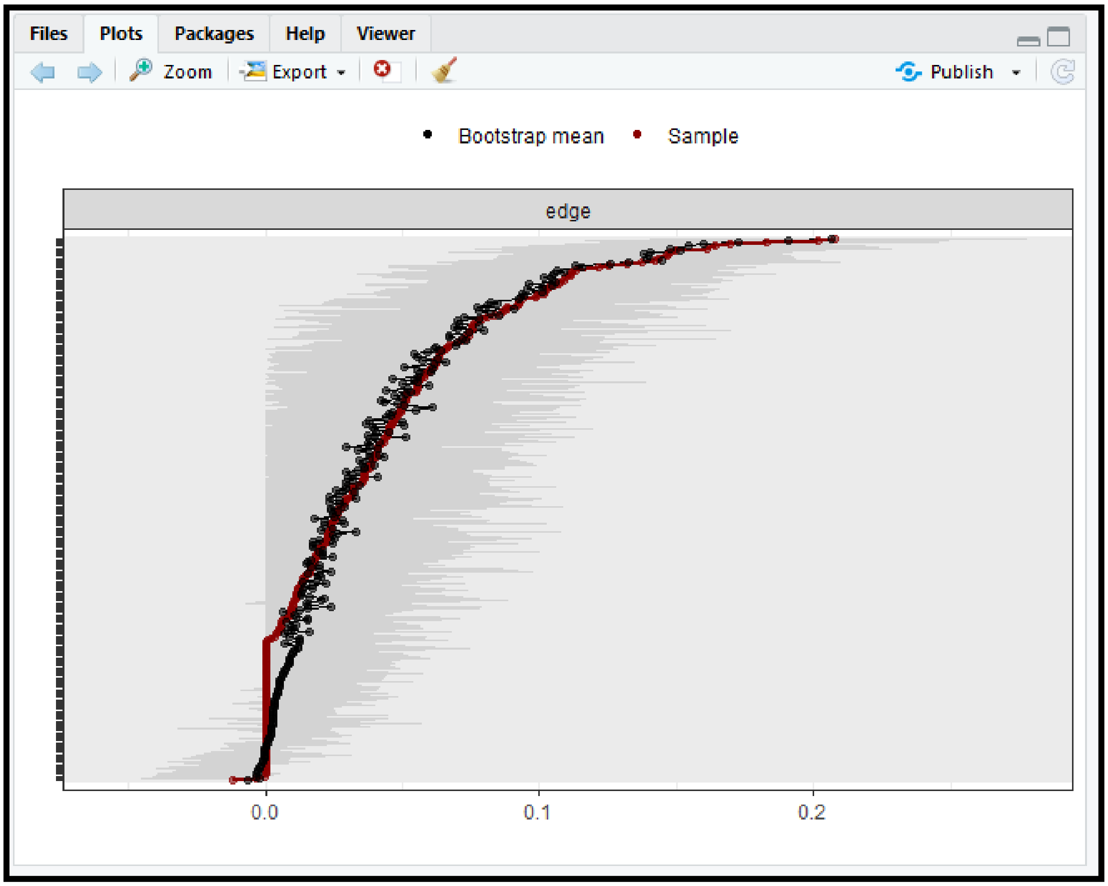


Figure 4.22 **Accuracy of the edge-weight estimates (red line) and the 95% confidence intervals (greybars) for the estimates.**

```
> summary(boot1)
# A tibble: 300 x 17
# Groups:   type, node1, node2 [300]
type  id    node1 node2 sample   mean      sd  CIlower CIupper     q2.5
<chr><chr><chr><chr><dbl><dbl><dbl><dbl><dbl><dbl>
1 edge  CT1-~ CT1   CT2   0.0983 1.01e-1 0.0303   3.77e-2 0.159    0.0354
2 edge  CT1-~ CT1   CT3   0.0496 4.08e-2 0.0272  -4.80e-3 0.104    0
3 edge  CT1-~ CT1   CT4   0.104  1.00e-1 0.0292   4.53e-2 0.162    0.0260
4 edge  CT1-~ CT1   GO1   0      2.53e-3 0.00623 -1.25e-2 0.0125  -0.00621
5 edge  CT1-~ CT1   GO2   0.0492 4.36e-2 0.0233   2.50e-3 0.0958   0.00144
6 edge  CT1-~ CT1   GO3   0      8.24e-4 0.00384 -7.69e-3 0.00769 -0.00259
7 edge  CT1-~ CT1   GO4   0.0565 5.73e-2 0.0249   6.73e-3 0.106    0.00408
8 edge  CT1-~ CT1   ORG1  0.0435 4.04e-2 0.0218  -4.60e-5 0.0870   0.00112
9 edge  CT1-~ CT1   ORG2  0.0504 4.64e-2 0.0278  -5.22e-3 0.106    0.00655
10 edge  CT1-~ CT1   ORG3  0.0881 8.18e-2 0.0271   3.39e-2 0.142    0.0218
# ... with 290 more rows, and 7 more variables: q97.5 <dbl>, q2.5_non0 <dbl>,
```

mean_non0 <*dbl*>, q97.5_non0 <*dbl*>, var_non0 <*dbl*>, sd_non0 <*dbl*>,
prop0 <*dbl*>

Interpretation: Since the class interval of most of the nodes does not contain zero within it, the null hypothesis is accepted and there is no significant difference in the order of the edge weights strength. The order of edge-weight strength must be considered with caution.

```
> boot2 <- bootnet(Network, nBoots = 50,type = "case", nCores = 8)
>plot(boot2)
```

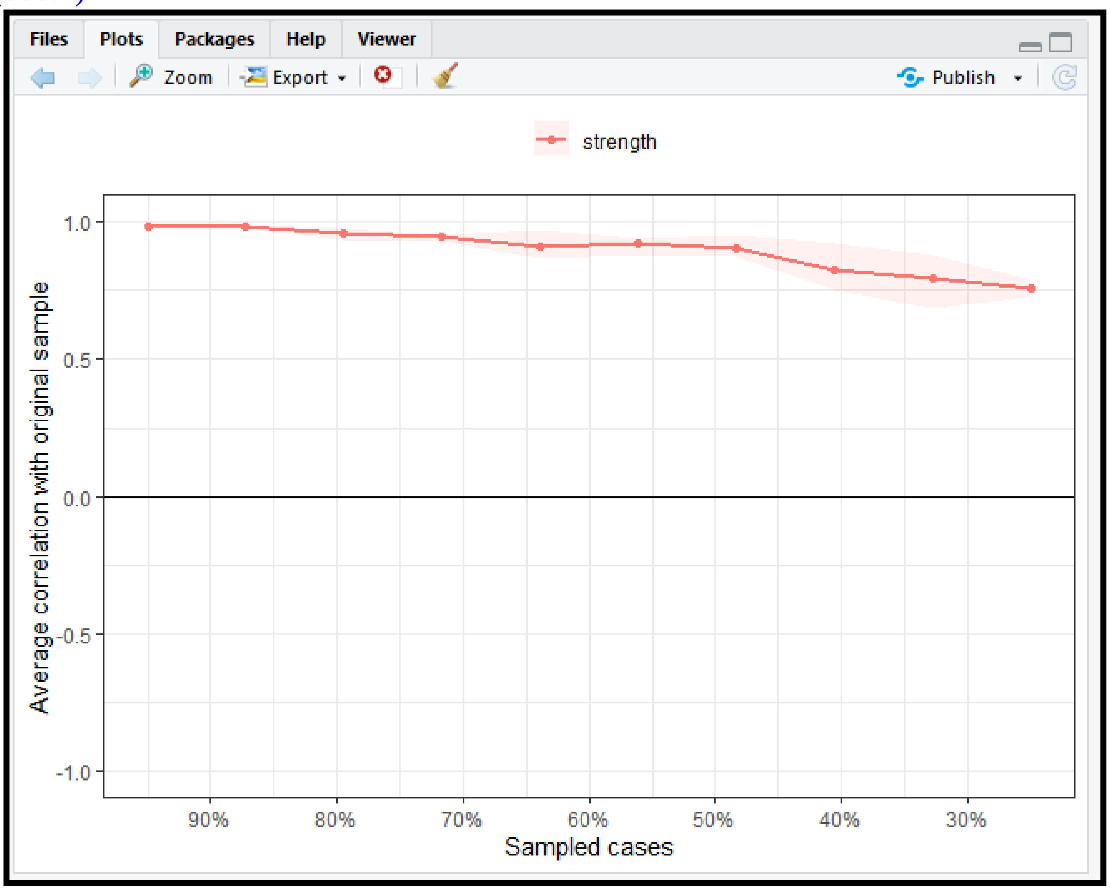


Figure 4.23 **Stability of Strength Centrality Index**

Interpretation: The figure shows that there is a gradual decrease in the strength of the edge weights when replicated across multiple samples generated through boot strapping, which indicates the occurance of split loading of the items of one sub-scale to another, but to a very slight extent since the fall in the curve is very small. Strength is the only centrality index in network analysis whose estimates are the most precisely calculated. The estimation of betweenness and closeness are possible only for larger samples (Santos et al., 2018).

```
> corStability(boot2)
=== Correlation Stability Analysis ===

Sampling levels tested:
nPerson Drop% n
1      450  75.0 2
2      590  67.2 4
3      730  59.4 6
4      870  51.6 6
5     1009  43.9 7
6     1149  36.1 4
7     1289  28.3 8
8     1429  20.6 7
9     1569  12.8 3
10    1709   5.0 3
```

Maximum drop proportions to retain correlation of 0.7 in at least 95% of the samples:

edge: 0.672

- For more accuracy, run bootnet(..., caseMin = 0.594, caseMax = 0.75)

strength: 0.75 (CS-coefficient is highest level tested)

- For more accuracy, run bootnet(..., caseMin = 0.672, caseMax = 1)

Accuracy can also be increased by increasing both 'nBoots' and 'caseN'.

Interpretation: The edge strength is above the acceptable benchmark of 0.5 at 0.672 and the CS-coefficient is higher than 0.7 benchmark at 0.75, implying that the correlation between the original factor structure and the bootstrapped structure is very high.

Reliability Analysis:

```
> boot <- bootEGA(MSLQ_SRL_Variables_Data, n = 50, model = "glasso", type = "resampling", plot.typicalStructure = FALSE)
> sc <- dimStability(boot, orig.wc = ega.MSLQ$wc)
> sc$dimensions
1     2
0.903 0.933
> sc$items$plot.itemStability
```

Interpretation: Since the structural consistency of the dimensions 1 and 2 is 0.903 and 0.933, it means that almost all the 9 items of motivation scale under self efficacy and goal orientation sub-scales and almost all the 12 items of learning strategies scale under critical thinking, organization and time and study environment sub-scales, retain their factor structure when found in multiple samples generated through boot strapping technique of 50 run.

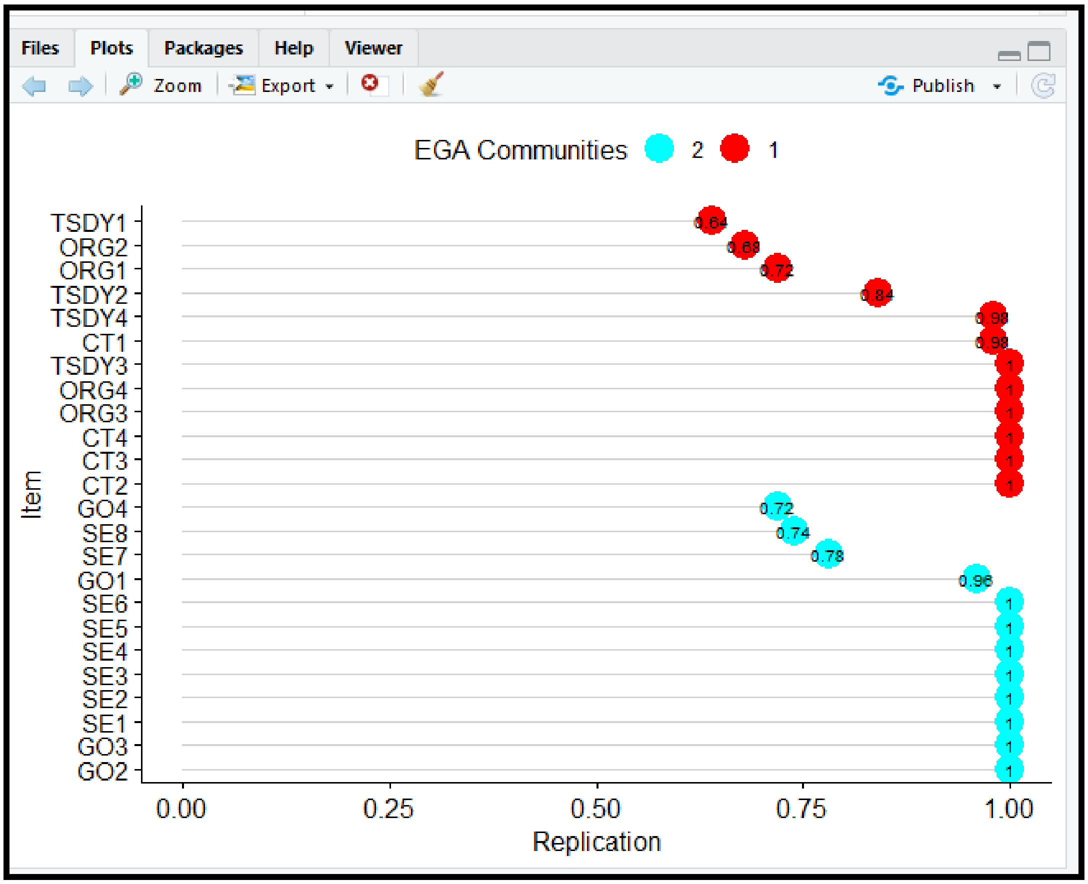


Figure 4.24 **Replication of the MSLQ Items**

Interpretation: The items which have the tendency to fall apart are TSDY1, TSDY2, ORG1, ORG2 of learning strategies scale and GO1, GO4, SE7 and SE8 items of motivation scale.Rest of the items are very strongly associated with their respective factor.

> View(sc$items$item.dim.rep)

Filter

	1	2	3
TSDY1	0.64	0.1	0.26
ORG2	0.68	0.06	0.26
ORG1	0.72	0.06	0.22
TSDY2	0.84		0.16
TSDY4	0.98		0.02
CT1	0.98		0.02
TSDY3	1		
ORG4	1		
ORG3	1		
CT4	1		
CT3	1		

Showing 1 to 11 of 24 entries

Console Terminal

~/

Filter

	1	2	3
CT2	1		
GO4	0.1	0.72	0.18
SE8	0.1	0.74	0.16
SE7	0.06	0.78	0.16
GO1		0.96	0.04
SE6		1	
SE5		1	
SE4		1	
SE3		1	
SE2		1	
SE1		1	

Showing 12 to 22 of 24 entries

GO3		1	
GO2		1	

Showing 14 to 24 of 24 entries

Interpretation: The variation of the items with the tendency to display falling apart, as discussed above, but across dimensions, is shown.

4.2.1.16 Validation of the Latent Variable Model of the Five Sub-scales of MSLQ used in this Research:

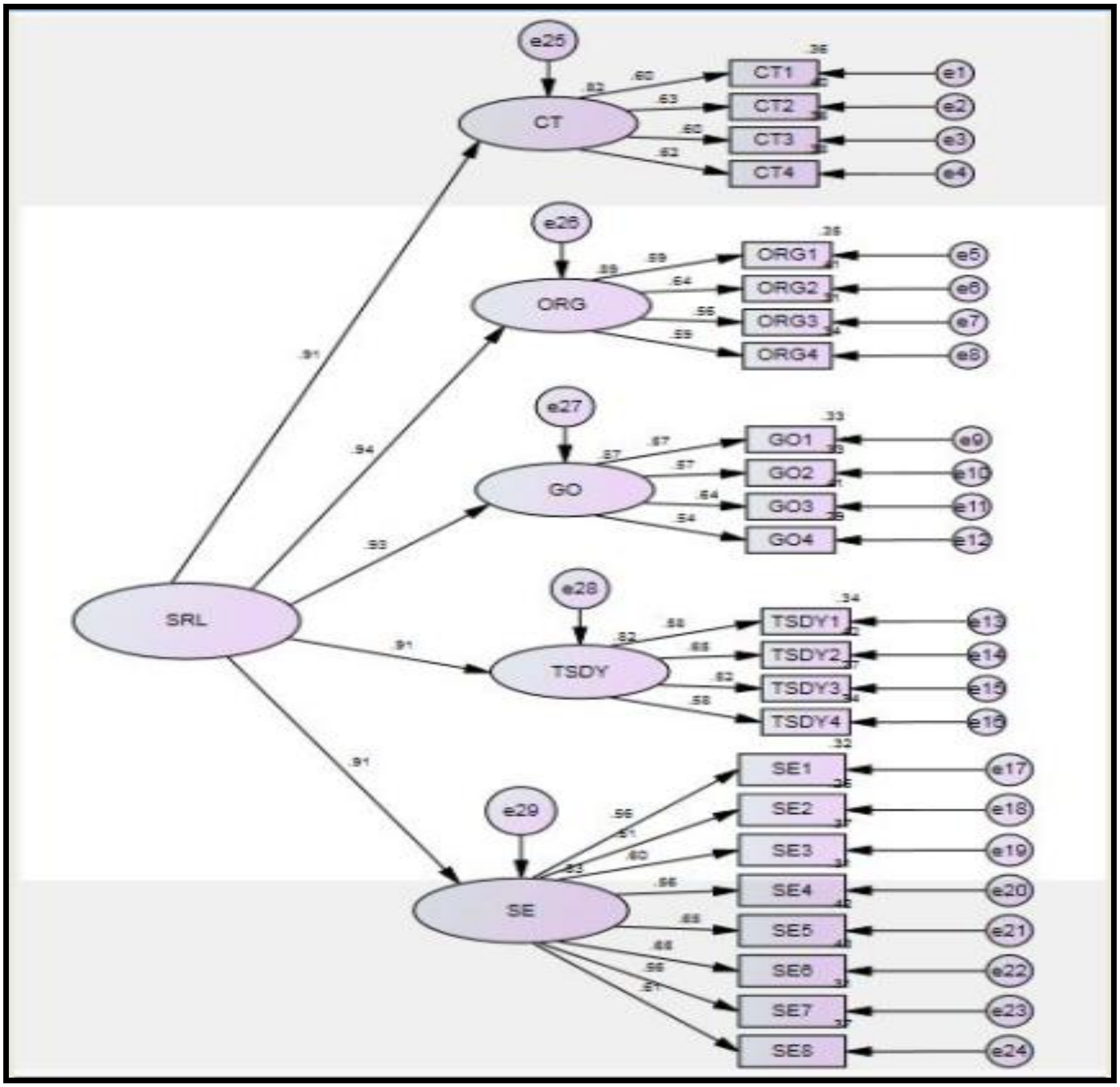


Figure 4.25 **Path Diagram the Latent Variable Model of the Five Sub-scales of MSLQ**

Table 4.84 Details of the First Order and Second Order Factor Loadings of MSLQ:

S.No.	Scale of MSLQ	Factor Loading on SRL	Item of MSLQ	Factor Loading on the Subscale	Cronbach's Alpha
1.	Critical Thinking (Learning Strategies)	0.91	CT1 – MSLQ 47	0.6	0.706
2.			CT2 - MSLQ 51	0.63	
3.			CT3 - MSLQ 66	0.6	
4.			CT4 - MSLQ 71	0.62	
5.	Organization (Learning Strategies)	0.94	ORG1 – MSLQ 32	0.59	0.687
6.			ORG2 – MSLQ 42	0.64	
7.			ORG3 – MSLQ 49	0.56	
8.			ORG4 – MSLQ 63	0.59	
9.	Goal Orientation (Motivation)	0.93	GO1 – MSLQ 1	0.57	0.67
10.			GO2 – MSLQ 16	0.57	
11.			GO3 – MSLQ 22	0.64	
12.			GO4 – MSLQ 24	0.54	
13.	Time and Study Environment (Learning Strategies)	0.91	TSDY1 – MSLQ 35	0.58	0.669
14.			TSDY2 – MSLQ 43	0.65	
15.			TSDY3 – MSLQ 65	0.62	
16.			TSDY4 – MSLQ 70	0.58	
17.	Self Efficacy (Motivation)	0.91	SE1 – MSLQ 5	0.56	0.808
18.			SE2 – MSLQ 6	0.51	
19.			SE3 – MSLQ 12	0.6	
20.			SE4 – MSLQ 15	0.56	

21.			SE5 – MSLQ 20	0.65	
22.			SE6 – MSLQ 21	0.65	
23.			SE7 – MSLQ 29	0.56	
24.			SE8 – MSLQ 31	0.61	

Interpretation: All the five chosen variables very strongly estimate their respective motivation and learning strategies components of self regulation learning as the factor loadings are above 0.9. This is because these sub-scales are themselves very strongly estimated their respective items with factor loadings ranging between 0.51 – 0.65. The reliability of the sub-scales are also acceptable above 0.6 (Kline, 1999) at 0.706, 0.687, 0.67, 0.669 and 0.808 respectively.

Table 4.85 Goodness of Fit Estimates of Five Sub-scales of MSLQ Used in the Present Study:

Estimates	CMIN/DF	RMR	GFI	TLI	CFI	RMSEA
Benchmark	<3	<0.08	>0.9	>0.9	>0.9	<0.08
Magnitude	4.406	0.085	0.949	0.926	0.933	0.044

Interpretation: The CMIN/DF value is higher than the benchmark 3 at 4.406. However,it is acceptable because this estimand is sensitive to low or high sample size, and the sample size of this study is large at 1799. The RMR estimate is close to its acceptable value at 0.085. The RMSEA is well within the acceptable range of 0.08 at 0.044. The fit indices, GFI, TLI and CFI, are well above the desired benchmark of 0.9, at 0.949, 0.926 and 0.933 values respectively. There is sufficient evidence to show that the chosen sub-scales of MSLQ possess stable factor structure through the satisfaction of their respective benchmark values.

4.2.1.17Validation of the Parsimonious Latent Variable Model of the Five Sub-scales of MSLQ used in this Research:

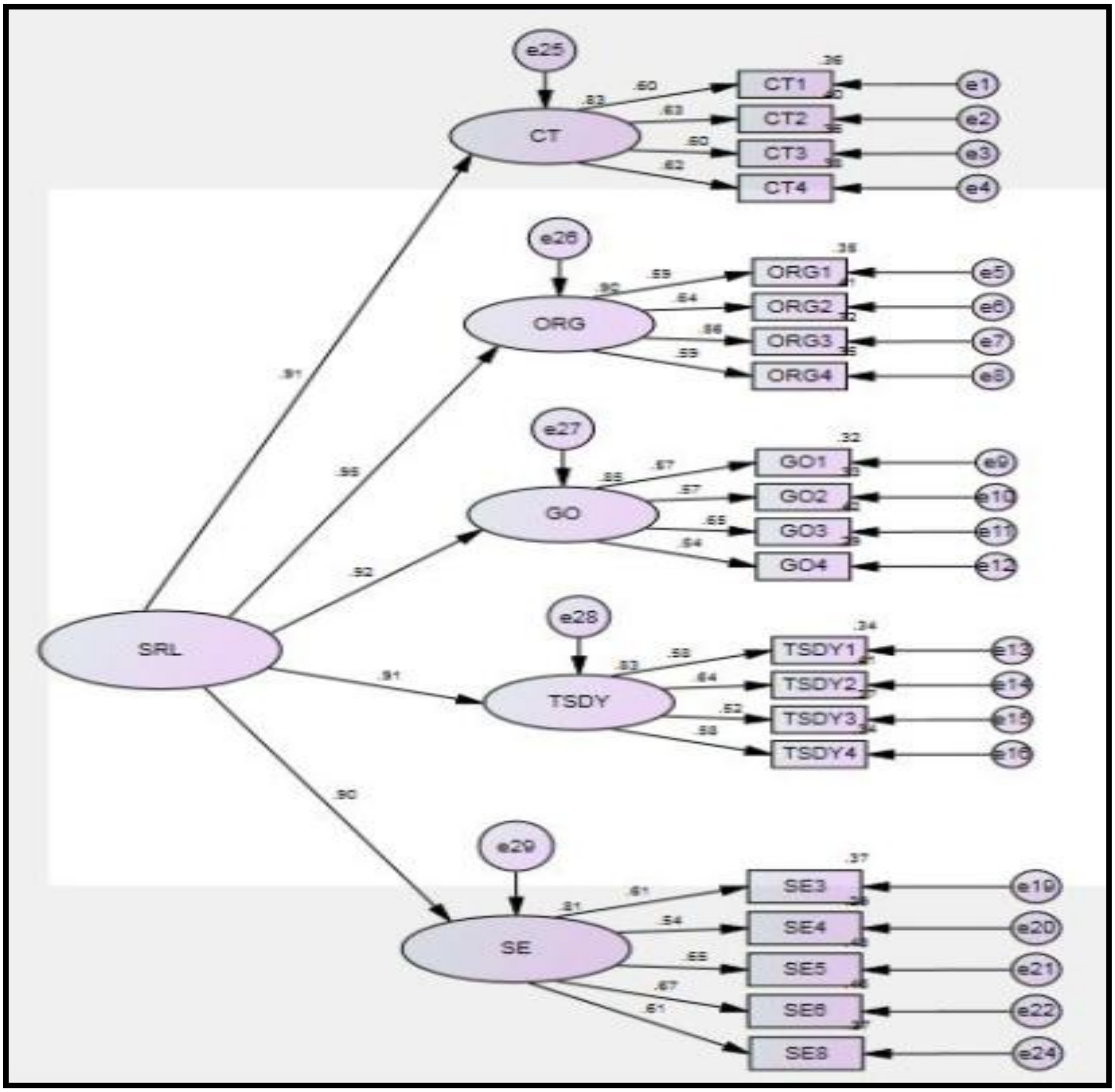


Figure 4.26 **Path Diagram of the Parsimonious Latent Variable Model of the Five Sub-scales of MSLQ**

Table 4.86 Details of the First Order and Second Order Factor Loadings of the Parsimonious Scales used in the Present Study:

S.No.	Scale of MSLQ	Factor Loading on SRL	Item of MSLQ	Factor Loading on the Subscale	Cronbach's Alpha
1.	Critical Thinking (Learning Strategies)	0.91	CT1 – MSLQ 47	0.6	0.706
2.			CT2 - MSLQ 51	0.63	
3.			CT3 - MSLQ 66	0.6	
4.			CT4 - MSLQ 71	0.62	
5.	Organization (Learning Strategies)	0.95	ORG1 – MSLQ 32	0.59	0.687
6.			ORG2 – MSLQ 42	0.64	
7.			ORG3 – MSLQ 49	0.56	
8.			ORG4 – MSLQ 63	0.59	
9.	Goal Orientation (Motivation)	0.92	GO1 – MSLQ 1	0.57	0.67
10.			GO2 – MSLQ 16	0.57	
11.			GO3 – MSLQ 22	0.65	
12.			GO4 – MSLQ 24	0.54	
13.	Time and Study Environment (Learning Strategies)	0.91	TSDY1 – MSLQ 35	0.58	0.669
14.			TSDY2 – MSLQ 43	0.64	
15.			TSDY3 – MSLQ 65	0.52	
16.			TSDY4 – MSLQ 70	0.58	
17.	Self Efficacy (Motivation)	0.90	SE1 – MSLQ 12	0.61	0.752
18.			SE2 – MSLQ 15	0.54	
19.			SE3 – MSLQ 20	0.65	
20.			SE4 – MSLQ 21	0.67	
21.			SE5 – MSLQ 31	0.61	

Interpretation: All the five chosen variables of the parsimonious structure very strongly estimate their respective motivation and learning strategies components of self regulation learning as the factor loadings are above 0.9. This is because these sub-scales are themselves very strongly estimated their respective items with factor loadings ranging between 0.52 – 0.65. The reliability of the sub-scales are also acceptable above 0.6 (Kline, 1999) at 0.706, 0.687, 0.67, 0.669 and 0.752 respectively.

Table 4.87 Goodness of Fit Estimates of Parsimonious Five Sub-scales of MSLQ Used in Present Study:

Estimates	CMIN/DF	RMR	GFI	TLI	CFI	RMSEA	AIC	BIC
Benchmark	<3	<0.08	>0.9	>0.9	>0.9	<0.08	1194.277	1195.772
Magnitude	4.794	0.087	0.953	0.927	0.936	0.046	976.019	977.184

Interpretation: The CMIN/DF value is higher than the benchmark 3 at 4.794. However,it is acceptable because this estimand is sensitive to low or high sample size, and the sample size of this study is large at 1799. The RMR estimate is close to its acceptable value at 0.087. The RMSEA is well within the acceptable range of 0.08 at 0.046. The fit indices, GFI, TLI and CFI, show improvement in the parsimonious model, and their estimates are well above the desired benchmark of 0.9, at 0.953, 0.927 and 0.936 values respectively. There is sufficient evidence to show that the chosen parsimonious sub-scales of MSLQ possess stable factor structure through the satisfaction of their respective benchmark values. Also, the lower AIC and BIC estimates of the parsimonious model, indicates it to be better a model, than the model with original items of the five subs-scales of MSLQ.

4.2.2 Validation of the Parsimonious Version of the Metacognitive Awareness Inventory in the Indian Context:

Flavell (1979) coined and defined metacognition as “thinking about thinking”, and refers to the use of certain capability of bring to use a taught strategy in the condition of need. Its relation with self regulated learning is well documented (Schneider and Lockl, 2002).The knowledge about metacogniton and the capability to regulate it are its two vital components (Flavell,1979; Cross and Paris, 1988; Paris and Winograd,1990; Whitebread et al.,2009; Schrew and Moshman, 1995; Schraw et al., 2006). From the perspective of self regulation, the regulation of this ability is more important than the knowledge. The most widely used instruments to measure the regulation of metacognition are the Motivated Strategies for Learning Questionnaire by Pintrinch et al. (1991) and the Metacognitive Awareness Inventory by Schraw and Dennison (1994). The 12 items pertaining to three dimensions of planning, self recording and self evaluation are clubbed as a subscale in MSLQ scale. On the contrary, the 20 items measuring the regulation part of metacognition, has 7 items specifically to measure planning, 7 items to measure self recording and 6 items to measure self evaluation. Owing to this specificity of items in measuring the dimensions of metacognition, the researcher selected this scale over MSLQ to measure the variable. The Metacognitive awareness inventory is dichotomous. However, the researcher extended the number of responses from two (yes or no) to five, by assigning 1=”Not at all tpical of me” to 5=”Very typical of me”. This exercise is in congruence to the findings of Comrey and Lee (1992) and Jones-Wiley, Restori and Lee (2007). Since the gradation of the response is raised, the performance of the scale in this new scenario requires validation. Moreover, this study also tried to develop a parsimonious version of the Metacognitive Awareness Inventory through scale purification since the scale primarily of foreign origin from Indian perspective (Churchill, 1979; Netemeyer et al., 2003; Jarvis et al., 2003). The tool was administered during regular class session, on 110 students of IInd year from the School of Mechanical Engineering, Lovely Professional University, Phagwara, India, selected through simple random sampling. The collected data was subjected to descriptive statistics, test of normality, confirmatory factor analysis, reliability analysis involving Cronbach’s alpha, Greatest lower bound reliability and Polychoric reliability. The goodness of fit of the original structure with 20 items is tested followed by the selection of the 11 items to form the parsimonious model with the factor loading of the items above 0.6 or 0.7 (Hair et al., 2006). The results are as follows:

Table 4.88 Descriptive Statistics - Planning:

	N	Mean	Std. Deviation	Skewness	Kurtosis
	Statistic	Statistic	Statistic	Statistic	Statistic
Plan2	105	3.6000	1.22945	-.457	-.834
Plan3	105	3.3810	1.25867	-.404	-.883
Plan5	105	3.3619	1.28694	-.322	-.927
Valid N (listwise)	105				

Table 4.89 Test of Normality – Planning:

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	Df	Sig.	Statistic	df	Sig.
Plan2	.189	105	.000	.878	105	.000
Plan3	.222	105	.000	.892	105	.000
Plan5	.176	105	.000	.896	105	.000

a. Lilliefors Significance Correction

Interpretation: Since the p-value for both then tests of normality is less than 0.05, it means that the result is significant. The null hypothesis of normal distribution of the data is rejected and its alterantive, meaning that the distribution of the data is not normal is accepted.

Table 4.9 Descriptive Statistics – Self Recording

	N	Mean	Std. Deviation	Skewness	Kurtosis
	Statistic	Statistic	Statistic	Statistic	Statistic
Srec10	105	3.2762	1.08747	-.207	-.408
Srec11	105	3.2286	1.17880	.010	-.963
Srec12	105	3.3238	1.18885	-.270	-.680
Srec14	105	3.3619	1.20993	-.334	-.865
Valid N (listwise)	105				

Table 4.91 Test of Normality – Self Recording

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	Df	Sig.	Statistic	df	Sig.
Srec10	.191	105	.000	.908	105	.000
Srec11	.167	105	.000	.906	105	.000
Srec12	.164	105	.000	.906	105	.000
Srec14	.215	105	.000	.900	105	.000

a. Lilliefors Significance Correction

Interpretation: Since the p-value for both then tests of normality is less than 0.05, it means that the result is significant. The null hypothesis of normal distribution of the data is rejected and its alterantive, meaning that the distribution of the data is not normal is accepted.

Table 4.92 Descriptive Statistics – Self Evaluation:

	N	Mean	Std. Deviation	Skewness	Kurtosis
	Statistic	Statistic	Statistic	Statistic	Statistic
Sevel15	105	3.4857	1.34532	-.392	-1.080
Sevel16	105	3.2476	1.26932	-.135	-1.033
Sevel18	105	3.2286	1.17880	-.241	-.697
Sevel20	105	3.3619	1.16952	-.303	-.769
Valid N (listwise)	105				

Table 4.93 Test of Normality – Self Evaluation:

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	Df	Sig.	Statistic	df	Sig.
Sevel15	.184	105	.000	.872	105	.000
Sevel16	.161	105	.000	.904	105	.000
Sevel18	.172	105	.000	.911	105	.000
Sevel20	.203	105	.000	.906	105	.000

a. Lilliefors Significance Correction

Interpretation: Since the p-value for both then tests of normality is less than 0.05, it means that the result is significant. The null hypothesis of normal distribution of the data is rejected and its alterantive, meaning that the distribution of the data is not normal is accepted.

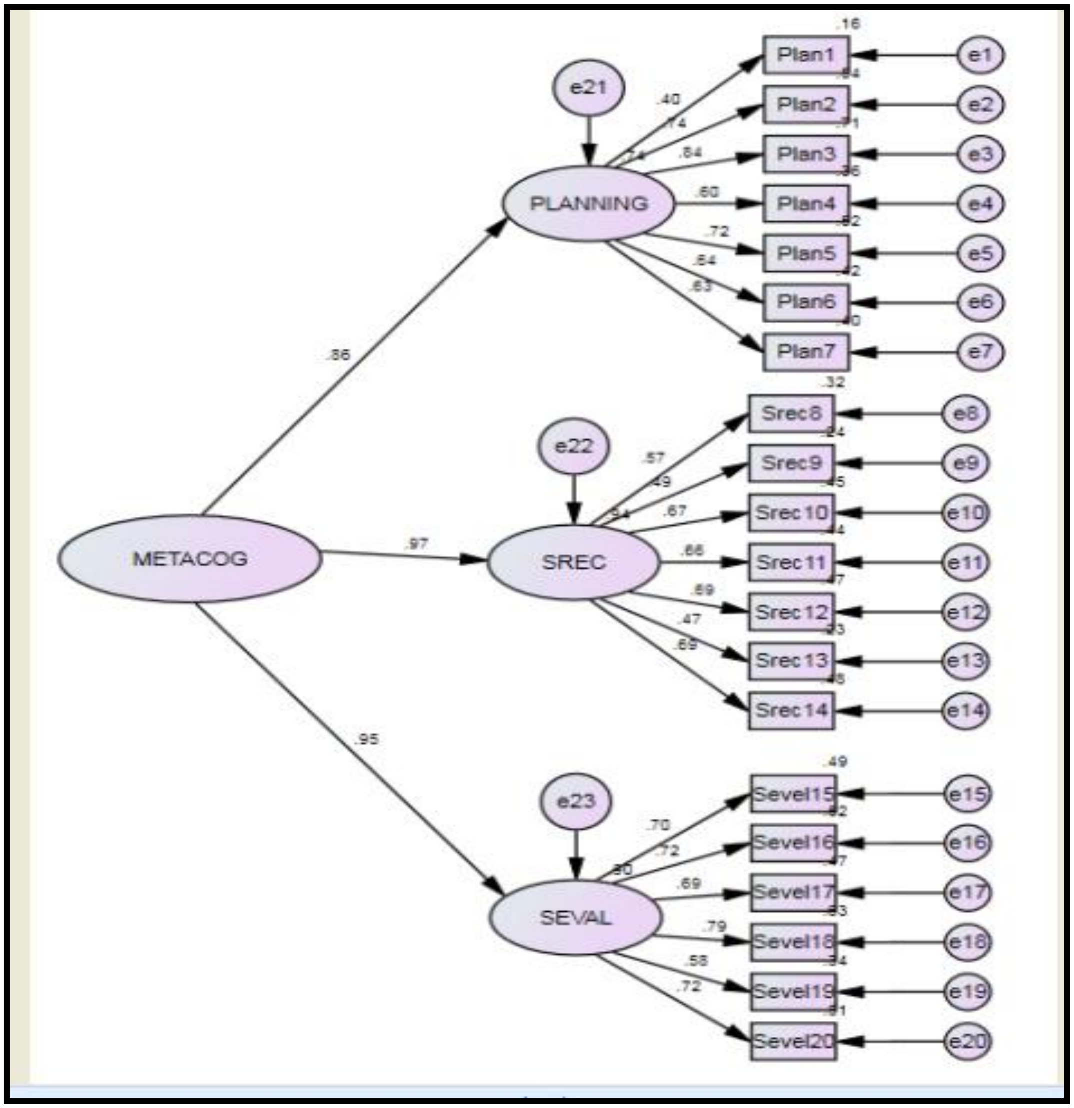


Figure 4.27 **Original Metacognition Awareness Inventory Scale Factor Structure:**

Table 4.94 Standardized Regression Weights of MAI:

			Estimate
PLANNING	<---	METACOG	.860
SREC	<---	METACOG	.968
SEVL	<---	METACOG	.948
Plan1	<---	PLANNING	.403
Plan2	<---	PLANNING	.735
Plan3	<---	PLANNING	.843
Plan4	<---	PLANNING	.604
Plan5	<---	PLANNING	.720
Plan6	<---	PLANNING	.644
Plan7	<---	PLANNING	.630
Srec8	<---	SREC	.569
Srec9	<---	SREC	.486
Srec10	<---	SREC	.674
Srec11	<---	SREC	.664
Srec12	<---	SREC	.689
Srec13	<---	SREC	.475
Srec14	<---	SREC	.691
Sevel15	<---	SEVL	.697
Sevel16	<---	SEVL	.720
Sevel17	<---	SEVL	.685
Sevel18	<---	SEVL	.794
Sevel19	<---	SEVL	.582
Sevel20	<---	SEVL	.716

All the twenty items belonging to the dimensions of planning, self recording and self evaluation loaded on their respective factor well indicating the validity of the factor structure of metacognition as per Schraw and Dannison (1994) work .

Table 4.95Goodness of Fit Measures of the Original MAI Scale Factor Structure:

Measure	P Value	CMIN/DF	RMSEA	IFI	TLI	CFI
Benchmark	>0.05	<3	<0.08	>0.9	>0.9	>0.9
Result	0.000	1.689	0.081	0.878	0.858	0.875

All the goodness of fit estimates are below their desired benchmark indicating a moderate goodness of fit of the original 20 items three fator structure of the metacognition awareness inventory in the Indian context.

Table 4.96: Reliability Analysis of the MAI Original Scale:

S.No.	Factor	Cronbach's Alpha	Greatest Lower Bound
1.	Planning	0.836	(0.884,1)
2.	Monitoring	0.801	(0.866,1)
3.	Self Evaluation	0.847	(0.883,1)

Since the dimensions did not follow normality and the factor loadings of their items were not same, the condition of tau-equivalence got violated leading to the underestimation of the true reliability of the scale by Cronbach's alpha (Raykov, 1997). As a result, the greatest lower bound reliability (Woodhouse and Jackson, 1977) is calculated using the FACTOR software (Lorenzo-Seva and Ferrando, 2006, 2013). The underestimation of the true reliability of the three dimensions by Cronbach's alpha is apparent. The true reliability of these scales lies way beyond the point estimation of alpha.

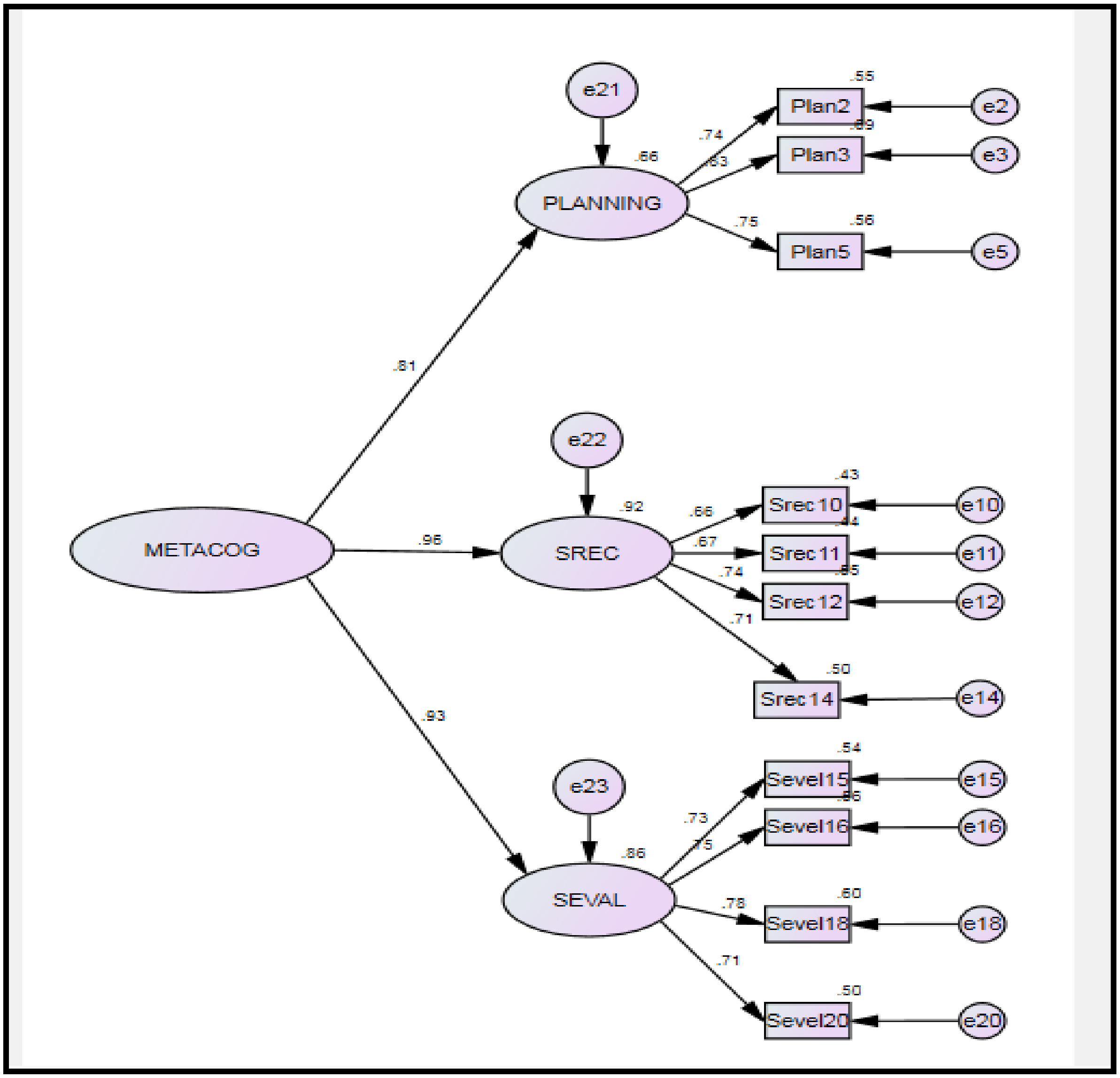


Figure4.28 **Parsimonious MAI Scale Factor Structure:**

Table 4.97 Standardized Regression Weights – Parsimonious Scale

			Estimate
PLANNING	<---	METACOG	.811
SREC	<---	METACOG	.960
SEVAL	<---	METACOG	.929
Plan2	<---	PLANNING	.745
Plan3	<---	PLANNING	.828
Plan5	<---	PLANNING	.749

			Estimate
Srec10	<---	SREC	.658
Srec11	<---	SREC	.665
Srec12	<---	SREC	.742
Srec14	<---	SREC	.710
Sevel15	<---	SEVAL	.733
Sevel16	<---	SEVAL	.746
Sevel18	<---	SEVAL	.776
Sevel20	<---	SEVAL	.711

All the eleven items belonging to the dimensions of planning, self recording and self evaluation loaded on their respective factor well indicating the validity of the parsimonious factor structure of metacognition.

Table 4.98Goodness of Fit Measures of the Parsimonious MAI Scale Factor Structure:

Measure	P Value	CMIN/DF	RMSEA	RMR	IFI	TLI	CFI
Benchmark	>0.05	<3	<0.08	<0.08	>0.9	>0.9	>0.9
Result	0.022	1.492	0.069	0.074	0.962	0.948	0.961

There are ample statistical evidences to confirm that the parsimonius three factor structure of metacognition as validated in the present study with its eleven items has excellent stability of its factor structure as all the estimates are satisfy the benchmark values of their respective estimands well in the Indian context, except p-value which is sensitive to the sample size of the study.

Table 4.99Reliability Analysis of the MAI Parsimonious Scale:

S.No.	**Factor**	**Cronbach's Alpha**	**Greatest Lower Bound**
1.	Planning	0.817	(0.818,1)
2.	Monitoring	0.786	(0.814,1)
3.	Self Evaluation	0.828	(0.86,1)

The excellent reliability estimates of the three factors planning, monitoring and self evaluation, and the underestimation of reliability by Cronbach's alpha is are apparemt in the table above. The factor self evaluation has highest reliability among the factors, followed by the factor planning. However, greatest lower bound reliability has the tendency to produce biased estimates of reliability when the sample size is less than 1000 (Ten Berge and Socan, 2004). Also, the responses of the modified metacognition awareness inventory are ordinal and not continuous in nature and call for the estimation of polychoric correlation based convariance matrix instead of pearson's product moment correlation (Muthen and Kaplan, 1985; 1992). As a result, the estimation of the true reliability is conducted by estimating the polychoric alpha and polychoric omega reliability of the scales using R/RStudio (Gadderman et al, 2012). The estimates preceded by their R codes are given below:

1. Import the data file in RStudio console using *Import Dataset*.
2. Install the package *Psych*
3. Library *Psych* # for activation of the package#
4. Polychoric(datafilename)
5. Exampledata<-polychoric(datafilename)
6. Alpha(exampledata$rho) # to estimate ordinal alpha
7. Omega(exampledata$rho) # to estimate ordinal omega

Table 4.100 Polychoric Alpha and Polychoric Omega of MAI:

S.No.	Factor	PolychoricAlpha Reliability	Polychoric Omega Reliability
1.	Planning	0.81	0.81
2.	Monitoring	0.77	0.8
3.	Self Evaluation	0.82	0.85

The three scales of metacognition under the rise in the gradation of the responses from two to five possessed very good reliability estimates above the accepted norm of 0.7, providing support to the previous works of Comrey and Lee (1992) and Jones-Wiley, Restori and Lee (2007) who mentioned that increasing the gradation of the responses improves the psychometrics of the instrument in general.

Table 4.101 Parsimony Comparisons – Original and Parsimonious MAI:

S.No.	Model of MAI	AIC	BIC
1.	Original (1994)	408.051	Not generated
2.	Parsimonious (2019)	111.178	111.7

It is evident that the parsimonious model of metacognitive awareness inventory with lesser Akieke Information Criterion (AIC) and Bayesian Information Criterion (BIC) estimates, is the better model when compared to its original counter part (Burnham and Anderson, 2004; Geiser, 2011).

Conclusion: The MAI (1994) tool is a very prevalent tool for the measurement of self regulation in college students across the world and in India as well, for conducting self regulation based research studies both at post graduation and doctoral level. However, owing to its foreign origin, a validation study was required. This study (Chakraborty and Chechi, 2019) achieved this objective and developed a parsimonious version of the tool as well. However, the study needs replication with higher sample size on multiple population in a culturally varied nation like India and conducting of measurement invariance testing with respect to gender and other demographic variables to establish further validity.

4.2.3 Validation of the Emotional Component of the Self Regulated Learning through Network Psychometrics Based Analysis of the Academic Emotional Regulation Questionnaire in the Indian Context:

Though the researchers in the field of education were aware of the role of emotions in academics, little specific and unreliable avenues of measurement, like the notoriously unstable test anxiety scale of MSLQ (1991) for measuring academic emotion only pertaining to examination, were available earlier. The contribution of Pekrun et al. (2002) is critical in this regard through the identification and presentation of various academic emotions in the literature. Means to measure the strategies employed by students to deal with the academic emotions experienced only during tests or examination were provided by Schutz et al. (2004) and Schutz, Benson and DeCuir (2008).

However, it was Buric et al., (2016) who developed the comprehensive academic emotional regulation questionnaire (AERQ), based on the theoretical work of Process model of emotional regulation (Gross, 1998) and the existing emotional regulation tool (Gross and John, 2003), which measures the strategies employed by University students to regulate the various emotions that arise during academic experiences. 37 items of this scale measure eight dimensions of this construct as mentioned below:

Table 4.102 Details of the Items and Dimensions of AERQ (2016):

Dimension. No.	Dimension Label	No. of Items	Description
1.	Redirecting Attention	6	“attempts to refocus one’s attention in order to avoid or to block the emotional experience”
2.	Venting	5	“students’ behavioural manifestations and expressions of unpleasant emotions as a way of releasing the negative energy”
3.	Situation selection	4	“circumventing academic situations that can trigger unpleasant emotions”
4.	Developing competencies	5	“behaviours and actions students implement to develop capabilities and competencies which will prevent or lessen unpleasant emotional experiences”
5.	Reappraisal	5	“students' attempts to undermine the relevance of a situation that evokes unpleasant emotions”
6.	Respiration	3	“students' attempts to reduce subjective feelings of tension accompanied by unpleasant emotions through deep breathing”
7.	Seeking Social Support	4	“sharing unpleasant emotions and seeking comfort from close members of the student's social milieu”
8.	Suppression	5	“students' attempts to suppress subjective and behavioural manifestations of unpleasant emotions in academic situations in order to

			hide them from others”

The researcher validated the original tool using structural equation modeling and re-validated the scale using the state of the art superior statistical technique of Network analysis (2017) approach of factor extraction and obtained fine results. Results of the two studies are presented below for evaluating the performance of the estimates, estimands and the estimators respectively in each of them.

4.2.3.1 Validation of the AERQ Scale in the Indian Context:

The sample for both the studies comprised of 496 students from the IInd and IIIrd year of School of Mechanical Engineering and School of Hotel Management and Tourism (330 boys and 5 girls from Mechanical engineering and 127 boys and 34 girls from Hotel management), of Lovely Professional University, selected through simple random sampling. The instrument was physically administered on the students during regular session of classes and after giving detailed instructions to them. The students took 25 to 30 minutes to respons to the questionnaire and returned it back to the researcher. The results obtained are discussed below, beginning with the reporting of the measures under descriptive statistics:

Table 4.103 Measures of Central Tendency, Dispersion and Asymmetry under Descriptive Statistics - AERQ:

Item	N	Mean	Std. Deviation	Skewness	Kurtosis
SitSelec1	496	2.3206	1.26653	.692	-.671
SitSelec2	496	2.6290	1.25508	.284	-1.115
SitSelec3	496	1.9093	.91554	1.148	1.219
SitSelec4	496	2.3589	1.15130	.639	-.455
DevCom1	496	3.4698	1.06130	-.710	-.029
DevCom2	496	4.0383	.95798	-1.323	1.903
DevCom3	496	3.3367	1.08504	-.423	-.458
DevCom4	496	3.7782	.93809	-.945	.977

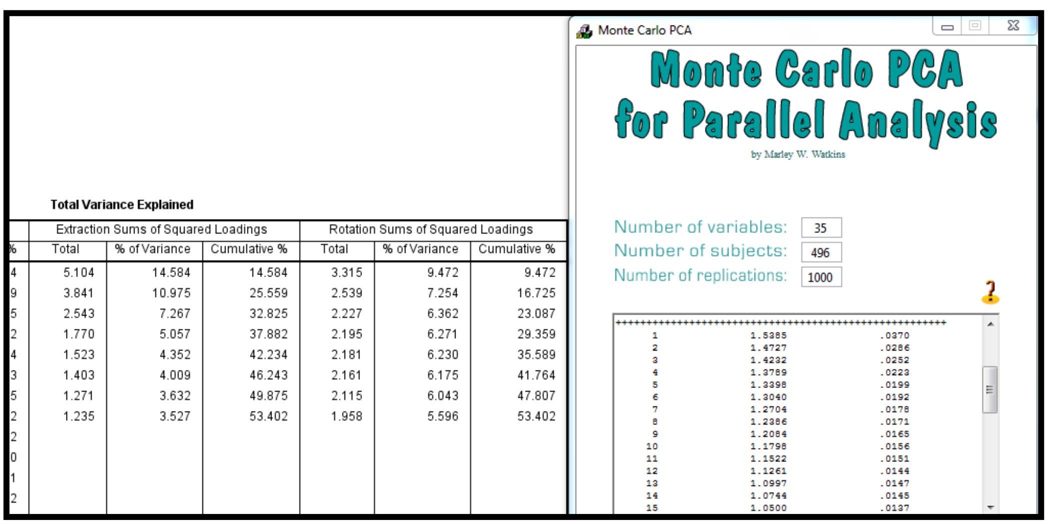
DevCom5	496	3.6613	1.02010	-.752	.045
ReAtt1	496	3.3992	.97541	-.449	-.291
ReAtt2	496	3.8508	1.05310	-.929	.412
ReAtt3	496	3.8750	1.00730	-.831	.178
ReAtt4	496	3.6452	1.07078	-.565	-.373
ReAtt5	496	3.7681	1.10859	-.765	-.114
ReAtt6	496	3.3145	1.10548	-.277	-.677
Reapp1	496	3.4032	1.30063	-.475	-.878
Reapp2	496	3.1855	1.25121	-.249	-1.011
Reapp3	496	3.5242	1.17182	-.505	-.657
Reapp4	496	3.7681	1.13381	-.688	-.348
Reapp5	496	3.0605	1.23598	-.006	-1.032
Supp1	496	3.3649	1.05692	-.296	-.481
Supp2	496	3.5222	1.08967	-.574	-.237
Supp3	496	3.6915	1.00685	-.652	.200
Supp4	496	3.4415	1.14442	-.493	-.501
Supp5	496	3.4637	1.13827	-.484	-.536
Respi1	496	3.7883	1.01779	-.767	.203
Respi2	496	3.6895	1.03688	-.705	.043
Respi3	496	3.5786	.99993	-.455	-.249
Venting1	496	2.3831	1.11121	.505	-.530
Venting2	496	2.1996	1.17485	.680	-.523
Venting3	496	2.5665	1.15977	.298	-.803
Venting4	496	2.2621	1.15464	.654	-.469
Venting5	496	2.4012	1.20030	.442	-.852
SocSupp1	496	3.6815	1.16139	-.748	-.197
SocSupp2	496	3.7258	1.07187	-.751	.034
SocSupp3	496	2.7843	1.23576	.094	-1.045
SocSupp4	496	3.5907	1.12269	-.589	-.401

Exploratory Factor Analysis:

All 37 items of the original scale were subjected to the first trial of exploratory factor analysis using the extraction method of “Principal component analysis” under “Varimax” rotation. Items with factor loading above 0.32 were to be retained in the correlation matrix (Tabachnick and Fidell, 2001), to be further considered for confirmatory factor analysis.

The sample size was adequate since the partial correlation coefficient KMO was above the benchmark value of 0.6 at 0.825.A significant result of Bartlett's sphericity indicated that the covariance correlation matrix has non-zero pearson's correlation coefficients through which factors could be explored. Nine such factors were generated with eigen value greater than 1 based on Kaiser's criterion explaining 54.227 % variance. However, two items from the dimension "Redirecting attention" (Item1 and Item 6) showedcross loading, removing of whom lead to the trial two of EFA.

In trial two, the KMO was sufficient at 0.822. The Bartlett's test of sphericity was significant. The construct's variance was well explained at 53.402 % by eight factors extracted using the Kaiser criterion of eigen value greater than 1 and through Hong's Parallel analysis performed through Watkins (2000) Monte Carlo PCA Parallel Analysis software. The eight factor in the software had its critical eigen value at 1.2 less than the eigen value of its counterpart generated by SPSS Statistics at 1.958. Finally, the original eight factors of AERQ measured through 35 of its original 37 items were obtained.



Total Variance Explained

	Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
%	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
4	5.104	14.584	14.584	3.315	9.472	9.472
9	3.841	10.975	25.559	2.539	7.254	16.725
5	2.543	7.267	32.825	2.227	6.362	23.087
2	1.770	5.057	37.882	2.195	6.271	29.359
4	1.523	4.352	42.234	2.181	6.230	35.589
3	1.403	4.009	46.243	2.161	6.175	41.764
5	1.271	3.632	49.875	2.115	6.043	47.807
2	1.235	3.527	53.402	1.958	5.596	53.402
2						
0						
1						
2						

Figure 4.29 **Hong's Parallel Analysis of AERQ EFA**

Table 4.104 Factor Loadings of the Extracted Eight Factors of AERQ:

Rotated Component Matrix[a]								
	Component							
	1	2	3	4	5	6	7	8
Venting5	.796							
Venting3	.781							
Venting2	.778							
Venting4	.740							
Venting1	.694							
Reapp3		.753						
Reapp5		.703						
Reapp2		.696						
Reapp4		.684						
Reapp1		.532						
Supp5			.684					
Supp4			.650					
Supp2			.634					
Supp1			.631					
Supp3			.523					
ReAtt2				.686				
ReAtt4				.674				
ReAtt5				.666				
ReAtt3				.652				
DevCom2					.640			
DevCom4					.632			
DevCom3					.609			
DevCom5					.590			
DevCom1					.483			

SocSupp4						.793		
SocSupp2						.788		
SocSupp1						.713		
SocSupp3	.404					.458		
Respi2							.812	
Respi3							.785	
Respi1							.745	
SitSelec1								.703
SitSelec3								.686
SitSelec2								.624
SitSelec4								.476
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.[a]								
a. Rotation converged in 7 iterations.								

SPSS AMOS software Ver. 23.0 was used to conduct confirmatory factor analysis. The selection of goodness of fit estimates like CMIN/DF(less than 3), RMR and RMSEA (less than 0.08) and GFI, IFI, TLI and CFI(greater than 0.93) (Leech et.al, 2008) was based on the recommendations of Kline (2004),.The lenient goodness of fit value at 0.9 is also mentioned in the literature (Bentler, 1990; Hays, Marshall et al., 1990; Barkoukis, Tsorbatzoudis, Grouios and Georgios, 2008). The path diagram the AERQ is shown below:

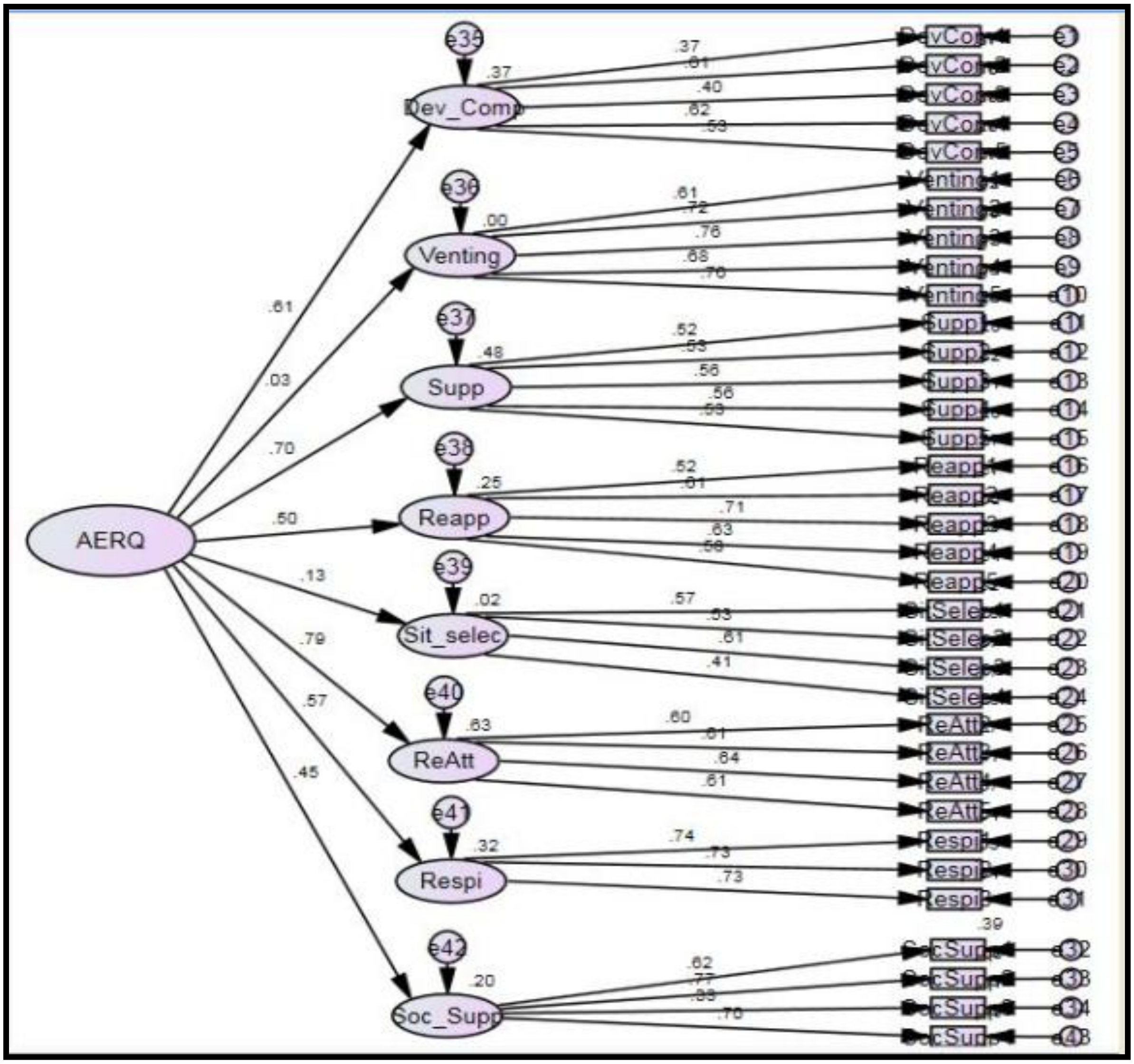


Figure 4.3 **Path Diagram of AERQ**

Table 4.105: Standardized Regression Weights of AERQ:

			Estimate
DevCom1	<---	Dev_Comp	.372
DevCom2	<---	Dev_Comp	.605
DevCom3	<---	Dev_Comp	.397
DevCom4	<---	Dev_Comp	.616
DevCom5	<---	Dev_Comp	.529

			Estimate
Venting1	<---	Venting	.607
Venting2	<---	Venting	.718
Venting3	<---	Venting	.762
Venting4	<---	Venting	.682
Venting5	<---	Venting	.763
Supp1	<---	Supp	.525
Supp2	<---	Supp	.526
Supp3	<---	Supp	.562
Supp4	<---	Supp	.561
Supp5	<---	Supp	.534
Reapp1	<---	Reapp	.519
Reapp2	<---	Reapp	.605
Reapp3	<---	Reapp	.707
Reapp4	<---	Reapp	.627
Reapp5	<---	Reapp	.580
SitSelec1	<---	Sit_selec	.569
SitSelec2	<---	Sit_selec	.533
SitSelec3	<---	Sit_selec	.609
SitSelec4	<---	Sit_selec	.410
ReAtt2	<---	ReAtt	.600
ReAtt3	<---	ReAtt	.609
ReAtt4	<---	ReAtt	.640
ReAtt5	<---	ReAtt	.610
Respi1	<---	Respi	.738
Respi2	<---	Respi	.725
Respi3	<---	Respi	.734
SocSupp1	<---	Soc_Supp	.622
SocSupp2	<---	Soc_Supp	.773
SocSupp3	<---	Soc_Supp	.331
SocSupp4	<---	Soc_Supp	.700

The factor loading of the 31 items out of the 35 items is above 0.5 (Brown, 2006) indicating strong association of the items with their respective factors.

Table 4.106 Goodness of Fit Estimates of theAERQ:

Estimate	p Value	CMIN/DF	RMR	RMSEA	GFI	IFI	TLI	CFI
Standards	>0.05	<3	<0.08	<0.05	>0.9	>0.9	>0.9	>0.9

Present Study (2019) Result	0.000	1.943	0.093	0.044	0.884	0.872	0.86	0.87
Original Study (2016) Result	0.01	2.09	0.07	0.06	-	-	-	0.85

All the fit indices estimates did not match up to their respective benchmarks, except RMSEA. Over all, the model showed moderate goodness of fit, better than the results of the original study (Buric et al., 2016). The possible reason for the obtaining of the moderate goodness of fit results akin to the original study as cited by its researchers is that the conventional fit indices prove to be very strict for measuring validity of multidimensional factor structures with items more than 5 (Marsh, Hau and Wen, 2004). The sensitivity of CFI estimate to small sample size should also be taken into consideration (Anderson and Gerbing, 1991; Kenny and McCoach, 2003). The obtained model similar to the original study did not use any modification indices to enhance results since such an exercise would curtail the reproduction of the results when the study would be conducted on subjects from different cultures and belonging to different academic levels, as correctly foresighted by Buric et al. (2016).

Table 4.107 Reliability Analysis of AERQ:

S.No.	Dimension	Item	Item-total Correlation	Cronbach's Alpha when Item Deleted	Composite Reliability
1.	Situation Selection	1	0.395	0.594 (0.508)	0.612
2.		2	0.382	0.594 (0.519)	
3.		3	0.458	0.594 (0.482)	
4.		4	0.296	0.594 (0.582)	
5.	Developing Competence	1	0.287	0.618 (0.609)	0.636
6.		2	0.441	0.618 (0.53)	
7.		3	0.320	0.618 (0.593)	
8.		4	0.459	0.618 (0.523)	
9.		5	0.372	0.618 (0.564)	
10.	Reappraisal	1	0.425	0.741 (0.728)	0.749
11.		2	0.531	0.741 (0.686)	

12.		3	0.585	0.741 (0.666)	
13.		4	0.492	0.741 (0.701)	
14.		5	0.497	0.741 (0.698)	
15.	Suppression	1	0.42	0.675 (0.628)	0.673
16		2	0.41	0.675 (0.632)	
17.		3	0.421	0.675 (0.628)	
18.		4	0.453	0.675 (0.612)	
19.		5	0.439	0.675 (0.619)	
20.	Respiration	1	0.596	0.776 (0.716)	0.777
21.		2	0.625	0.776 (0.684)	
22.		3	0.615	0.776 (0.695)	
23.	Venting	1	0.547	0.833 (0.822)	0.824
24.		2	0.653	0.833 (0.793)	
25.		3	0.676	0.833 (0.787)	
26.		4	0.609	0.833 (0.806)	
27.		5	0.676	0.833 (0.787)	
28.	Social Support	1	0.471	0.683 (0.615)	0.707
29.		2	0.562	0.683 (0.56)	
30.		3	0.29	0.683 (0.735)	
31.		4	0.575	0.683 (0.547)	
32.	Redirecting Attention	2	0.488	0.708 (0.649)	0.709
33.		3	0.49	0.708 (0.648)	
34.		4	0.509	0.708 (0.636)	
35.		5	0.49	0.708 (0.649)	

The underestimation (Raykov, 1997; Graham, 2006) of the popular estimate of internal consistency (Sijtsma, 2009; Peters, 2014), Cronbach's alpha (1951) on the violation of tau equivalenve, normality of the data, equal loading of the items on the factors (Teo and Fan, 2013) and the unidimensionality of the measured construct (Green and Yang, 2009) are addressed in this study by computing Raykov's composite reliability (1997) of the eight dimensions of AERQ. Raykov's composite reliability measures the reliability of congeneric models with items possessing varying factor loadings as is the case more often than not, and is free from the shortcomings of Cronbach alpha's erroneous estimation of true reliability of the scales.

The apparent under estimation of reliability by the Cronbach's alpha and the acceptable composite reliability estimates of all the eight sub-scales of AERQ above 0.6 (Kline, 1999) of this study (Chakraborty and Chechi, 2020a) are shown above.

4.2.3.2 Network Psychometrics Based Validation of AERQ in the Indian Context:

Addessing the shortcomings of the traditional factor analysis technique, Golino and Demetriou (2017) developed a powerful technique of graphically extracting factors of psychological variables called as the exploratory graph analysis (EGA; Golino and Epskamp, 2016) evolving from the field of Network Psychometrics. To the best of the knowledge of the researcher, the application of this technique of tool validation in Education in the Indian context, is reported and discussed first in this study Chakraborty and Chechi (2020b) with the following statistical techniques, R codes and results:

Statistical Techniques:

In order to weed out the outliers from the data, Mahalanobis distance was estimated using SPSS Statistics Ver. 23.0. This resulted in the reduction of the sample size of the study to 443 from 496. The remaining state of the art statistical analysis was performed using the functions of R Ver. 3.6.3 and RStudio Ver. 6.1.7601. The package *eganet* (Golino et al., 2020) was used to conduct exploratory graph analysis. The packages*lavaan* (Rossel, 2012), and *Psych* (Revelle, 2019), using the estimator "WLSMV" for ordinal data, and its robust goodness of fit estimates, were used for Confirmatory factor analysis. In network analysis based statistical inference analysis, the accuracy and significance of the edge weight of the nodes of the network were estimated using non-parametric bootstrap confidence interval, correlation stability coefficient and bootstrapped difference tests through the package *bootnet*. Internal consistency based reliability estimation is replaced by Structural consistency computation in network using the packages *bootega*, *eganet*(Golino and Christensen, 2020) and *psych*. The plots of this study are generated by the package *qgraph*Epskamp, 2020).

Results:

R Codes andResults of Exploratory Graph Analysis – Trail 1:

1. Read the data file in RStudio, say, AERQ_37_ALL.
2. Install the package *eganet*.
3. Library (*eganet*) - Activate the package eganet.
4. Define the data frame ega.aerq to store the result of exploratory graph analysis
5. Display the results using summary command

View(AERQ_37_ALL)

> ega.aerq<-EGA(AERQ_37_ALL, plot.EGA = TRUE)

>summary(ega.aerq)

EGA Results:

Number of Dimensions:

[1] 8

Items per Dimension:
items dimension
Vn1 Venting1 1
Vn2 Venting2 1
Vn3 Venting3 1
Vn4 Venting4 1Vn5 Venting5 1
ScS3 SocSupp31
DC1 DevCom1 2
DC2 DevCom2 2
DC3 DevCom3 2
DC4 DevCom4 2
DC5 DevCom5 2
StS1 SitSelec1 3
StS2 SitSelec2 3
StS3 SitSelec3 3
StS4 SitSelec4 3
Rs1 Respi1 4
Rs2 Respi2 4
Rs3 Respi3 4
Sp1 Supp1 5
Sp2 Supp2 5
Sp3 Supp3 5
Sp4 Supp4 5
Sp5 Supp5 5
Rp1 Reapp1 6

Rp2	Reapp2	6
Rp3	Reapp3	6
Rp4	Reapp4	6
Rp5	Reapp5	6
ScS1	SocSupp17	
ScS2	SocSupp27	
ScS4	SocSupp47	
RA1	ReAtt1	8
RA2	ReAtt2	8
RA3	ReAtt3	8
RA4	ReAtt4	8
RA5	ReAtt5	8
RA6	ReAtt6	8

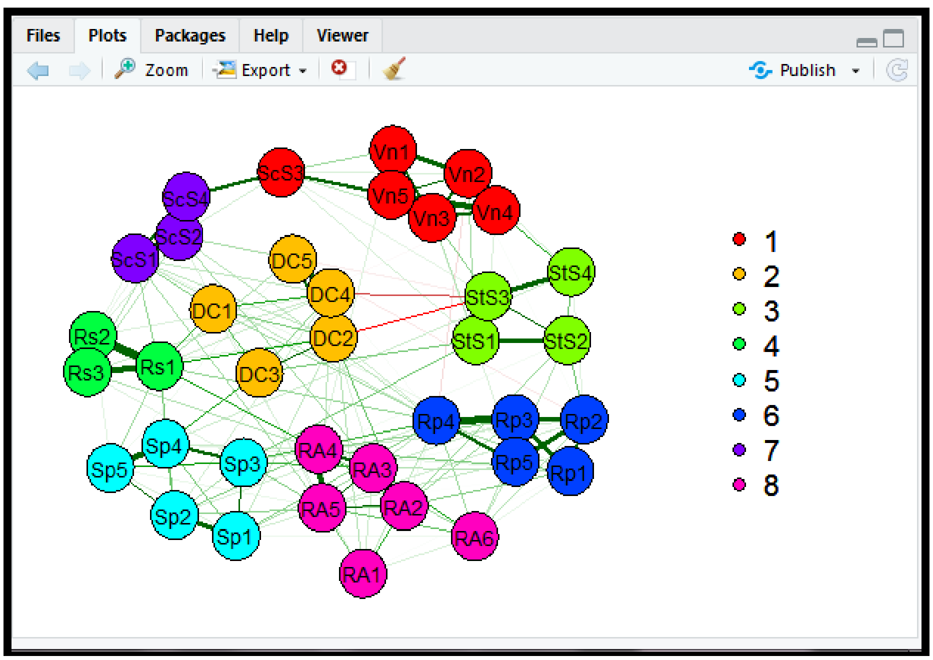


Figure 4.31 **Network of partial correlations, estimated using graphical lasso, showing the pattern of AERQ items per cluster. Cluster 1 = Venting, Cluster 2 = Developing competencies, Cluster 3 = Situation Selection, Cluster 4 = Respiration, Cluster 5 = Suppression, Cluster 6 = Reappraisal, Cluster 7 = Social Support, Cluster 8 = Redirecting Attention**

Interpretation: The item 3 of the dimension Social support showed cross loading. It is eliminated to re-run the exploratory graph analysis which extracted the original eight factors structure of AERQ, with the remaining 36 items of the scale loading aptly in their respective factors.

R Codes / Results of Exploratory Graph Analysis – Final Trail

```
>View(AERQ_37_ALL_Without_Outliers_and_Item_SocSup3)
>ega.aerq<-EGA(AERQ_37_ALL_Without_Outliers_and_Item_SocSup3, plot.EGA = TRUE)
>summary(ega.aerq)
EGA Results:

Number of Dimensions:
[1] 8

Items per Dimension:
items dimension
DC1    DevCom1    1
DC2    DevCom2    1
DC3    DevCom3    1
DC4    DevCom4    1
DC5    DevCom5    1
StS1 SitSelec1       2
StS2 SitSelec2       2
SS3  SitSelec3       2
StS4 SitSelec4       2
Sp1      Supp1        3
Sp2      Supp2        3
Sp3      Supp3        3
Sp4      Supp4        3
Sp5      Supp5        3
Rs1     Respi1        4
Rs2     Respi2        4
Rs3     Respi3        4
Rp1     Reapp1        5
Rp2     Reapp2        5
Rp3     Reapp3        5
Rp4     Reapp4        5
Rp5     Reapp5         5
ScS1  SocSupp16
ScS2  SocSupp26
ScS4  SocSupp46
RA1     ReAtt1         7
RA2     ReAtt2         7
```

RA3	ReAtt3	7
RA4	ReAtt4	7
RA5	ReAtt5	7
RA6	ReAtt6	7
Vn1	Venting1	8
Vn2	Venting2	8
Vn3	Venting3	8
Vn4	Venting4	8
Vn5	Venting5	8

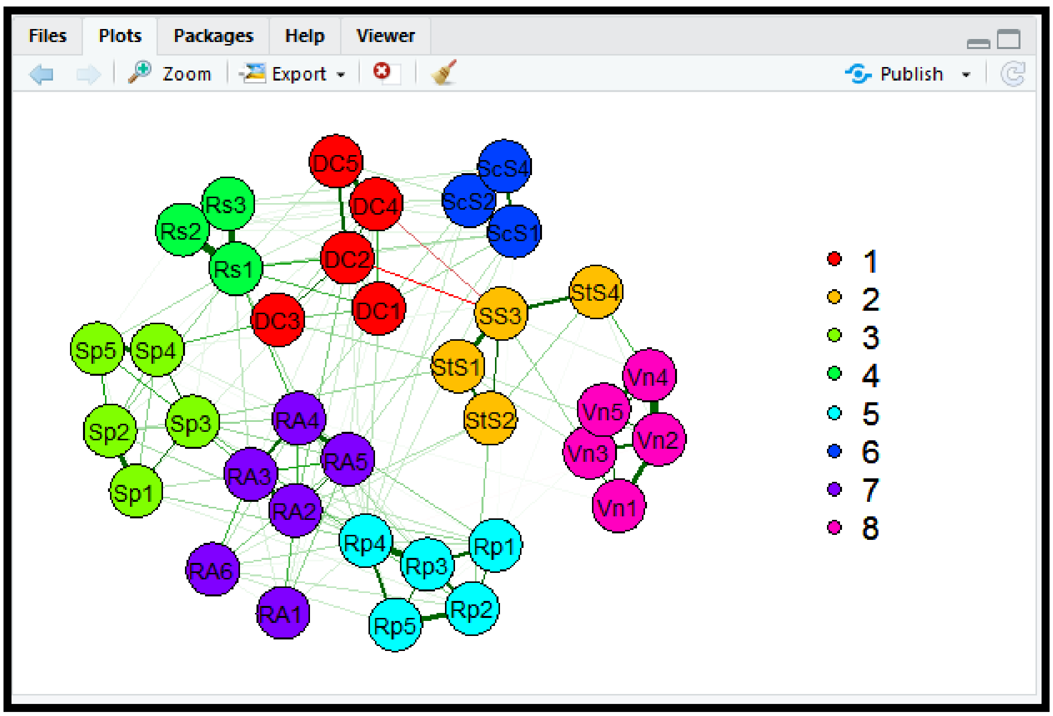


Figure 4.32 **Network of partial correlations, estimated using graphical lasso, showing the final pattern of AERQ items per cluster. Cluster 1 = Venting, Cluster 2 = Developing competencies, Cluster 3 = Situation Selection, Cluster 4 = Respiration, Cluster 5 = Suppression, Cluster 6 = Reappraisal, Cluster 7 = Social Support, Cluster 8 = Redirecting Attention**

R Codes / Results for Conducting WLSMV Estimator based Confirmatory Factor Analysis for Ordinal Data to obtain Factor Loadings and Goodness of Fit Measures:

```
>cfa.aerq <- CFA(ega.obj = ega.aerq, estimator = 'WLSMV', plot.CFA = TRUE, data = AERQ_37_ALL_Without_Outliers_and_Item_SocSup3)
```

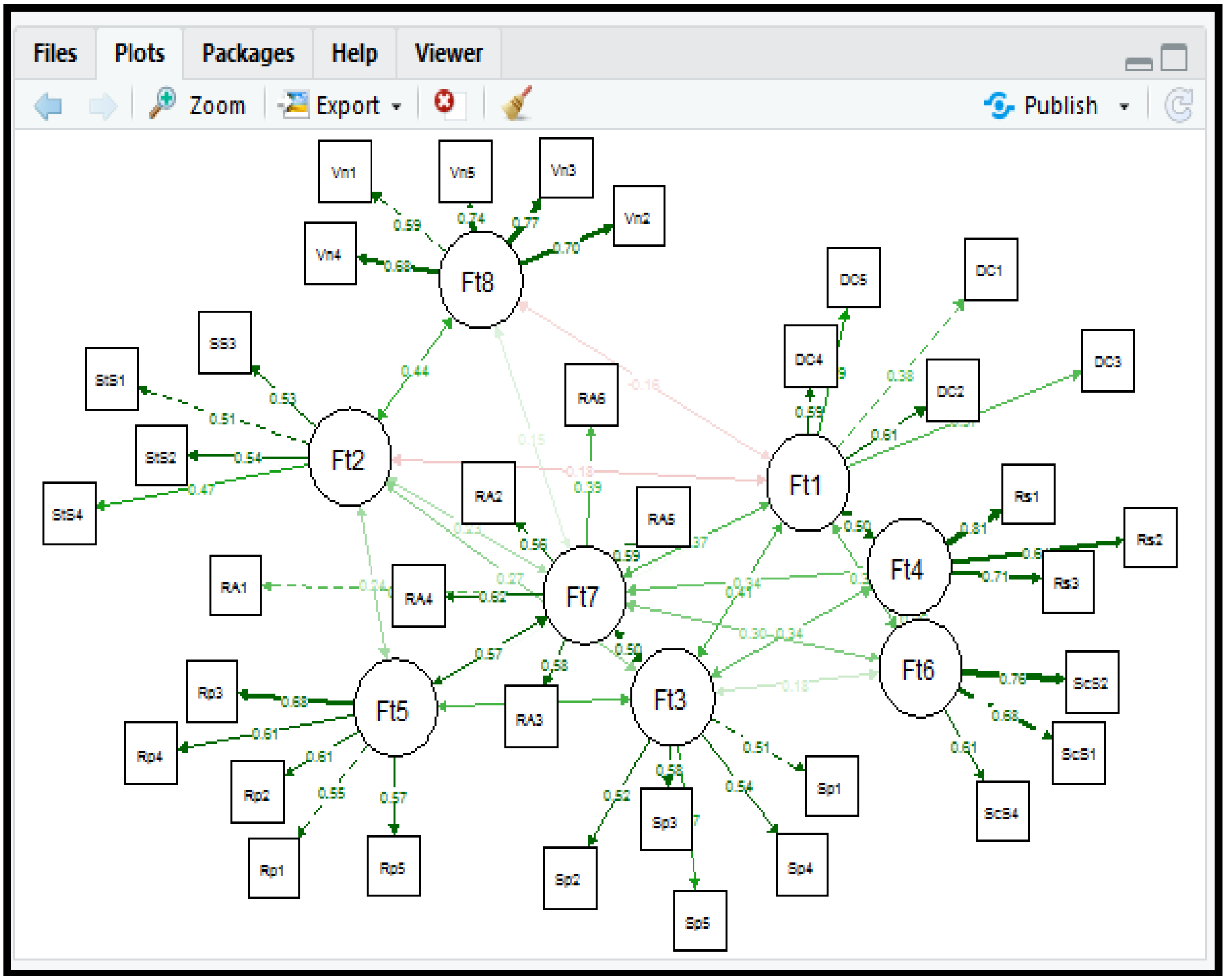


Figure 4.33 **Standardized weights of the CFA model from the Structure Suggested by EGA in the AERQ.**

>>lavaan::fitMeasures(cfa.aerq$fit, fit.measures = "all")

npar fmin
100.000 0.639
chisq df
565.982 566.000
pvalue chisq.scaled
0.492 819.833
df.scaled pvalue.scaled
566.000 0.000
chisq.scaling.factor baseline.chisq
0.690 5287.523
baseline.df baseline.pvalue

630.000 0.000
baseline.chisq.scaled baseline.df.scaled
5287.523 630.000
baseline.pvalue.scaled baseline.chisq.scaling.factor
0.000 1.000
cfi tli
1.000 1.000
nnfi rfi
1.000 0.881
nfi pnfi
0.893 0.802
ifi rni
1.000 1.000
cfi.scaled tli.scaled
0.946 0.939
cfi.robust tli.robust
0.962 0.958
nnfi.scaled nnfi.robust
0.939 0.958
rfi.scaled nfi.scaled
0.827 0.845
ifi.scaled rni.scaled
0.946 0.946
rni.robust**rmsea**
0.962 **0.000**
rmsea.ci.lower rmsea.ci.upper
0.000 0.015
rmsea.pvalue rmsea.scaled
1.000 0.032
rmsea.ci.lower.scaled rmsea.ci.upper.scaled
0.026 0.037
rmsea.pvalue.scaled **rmsea.robust**
1.000 **0.026**
rmsea.ci.lower.robust rmsea.ci.upper.robust
0.022 0.030
rmsea.pvalue.robust rmr
NA 0.063
rmr_nomean**srmr**
0.063 **0.048**
srmr_bentler srmr_bentler_nomean
0.048 0.048
crmr crmr_nomean
0.049 0.049
srmr_mplus srmr_mplus_nomean

0.048 0.048
cn_05 cn_01
487.102 506.425
gfi **agfi**
0.964 **0.958**
pgfi mfi
0.819 1.000
ecvi
1.733

Table 4.108Result of Confirmatory Factor Analysis for Ordinal Data using WLSMV estimator:

S.No.	Estimate	Benchmark of the Estimate	Standard MI based Estimate	Robust WLSMV based Estimate	Remark on Goodness of Fit
1.	CFI	0.95	0.946	0.962	Excellent
2.	TLI	0.95	0.939	0.958	Excellent
3.	GFI / AGFI	0.95	NA	0.964 / 0.958	Excellent
4.	RMSEA	0.08	0.000	0.026	Excellent
5.	SRMR	0.05	0.048	0.048	Excellent

Interpretation: The network analysis based confirmatory analysis of the goodness of fit estimation based on Weighted Least Sqaure Mean and Variance (WLSMV) estimator for ordinal Likert scale type responses, in addition to Maximum Likelihood (MI) estimator based goodness of fit estimates, produced excellent estimates of the graph model of AERQ. The ML estimator can be used when the data is normal and the responses are continuous. But generally, the data collected using questionnaire has ordinal category responses and the data is not normal. Under such circumstances, the estimation of goodness of fit can be better estimated through the polychoric covariance matrix instead of the Pearson’s correlation based covariance matrix (Suh, 2015). Using this new WLSMV estimator, the obtained CFI, TLI and GFI/AGFI are well above the benchmark mark of 0.95 at 0.962, 0.958 and 0.964/0.958 showing very good goodness of fit. The root mean square error of approximation and standard root mean residual estimand's estimates are also as desired to be below 0.08 benchmark at 0.026 and 0.048 respectively. All the estimates confirm the eight dimensional factor structure of the academic emotional regulation questionnaire factor structure in the Indian context.

```
>View(ega.aerq$dim.variables)
>net.loads(ega.aerq$network, ega.aerq$wc)$std
1     2     3     4     5     6     7     8
SitSelec1  0.040  0.033  0.262  0.000 0.033  0.000  0.000 0.000
SitSelec2  0.000  0.000  0.261  0.000 0.003  0.031  0.000 0.038
SitSelec3  0.037 -0.124  0.362  0.000 0.000  0.000 -0.005 0.000
SitSelec4  0.055  0.000  0.165  0.000 0.012  0.006  0.000 0.000
DevCom1    0.000  0.132  0.000  0.058 0.000  0.020  0.033 0.008
DevCom2    0.000  0.297 -0.087  0.081 0.014  0.011  0.018 0.040
DevCom3    0.000  0.149  0.038  0.000 0.057  0.000  0.000 0.000
DevCom4    0.000  0.314 -0.050  0.038 0.011  0.002  0.018 0.028
DevCom5    0.000  0.234 -0.003  0.022 0.004 -0.005  0.024 0.000
ReAtt1     0.000  0.027  0.000  0.000 0.000  0.015  0.000 0.095
ReAtt2     0.000  0.037  0.029  0.000 0.027  0.052  0.000 0.285
ReAtt3     0.000  0.009  0.000  0.020 0.069  0.044  0.028 0.320
ReAtt4     0.006  0.000  0.000  0.067 0.042  0.064  0.000 0.269
ReAtt5     0.000  0.015  0.000  0.000 0.034  0.026  0.037 0.309
ReAtt6     0.000  0.000  0.020  0.000 0.004  0.058  0.000 0.112
Reapp1     0.000  0.000  0.000  0.000 0.007  0.203  0.006 0.077
Reapp2     0.001 -0.006  0.047  0.000 0.011  0.319  0.000 0.037
Reapp3     0.000  0.000  0.000  0.000 0.012  0.404  0.000 0.055
Reapp4    -0.007  0.036  0.000  0.028 0.086  0.281  0.037 0.057
Reapp5     0.007  0.000  0.000  0.000 0.000  0.276  0.000 0.027
Supp1      0.000  0.015  0.000  0.000 0.240  0.036  0.000 0.022
Supp2      0.000  0.011  0.003  0.037 0.248  0.010  0.000 0.050
Supp3      0.000  0.000  0.038  0.009 0.250  0.053  0.000 0.069
Supp4      0.000  0.058  0.014  0.007 0.293  0.006  0.000 0.011
Supp5      0.000  0.004  0.000  0.033 0.269  0.000  0.000 0.004
Respi1    -0.001  0.150  0.000  0.343 0.063  0.023  0.030 0.050
Respi2     0.000  0.009  0.000  0.402 0.006  0.000  0.025 0.000
Respi3     0.000  0.023  0.000  0.372 0.008  0.000  0.040 0.020
Venting1   0.257  0.000  0.000  0.000 0.000  0.000  0.000 0.007
Venting2   0.382  0.000  0.034  0.000 0.000  0.009  0.000 0.000
Venting3   0.388  0.000  0.055  0.000 0.000  0.008  0.000 0.000
Venting4   0.310  0.000  0.074 -0.002 0.000  0.000  0.000 0.000
Venting5   0.460  0.000  0.000  0.000 0.000  0.000  0.000 0.000
SocSupp1   0.000  0.059  0.000  0.036 0.000  0.018  0.310 0.020
```

SocSupp2	0.009	0.021	-0.005	0.030	0.000	0.015	0.439	0.028
SocSupp3	0.120	0.000	0.020	0.000	0.000	0.000	0.128	0.000
SocSupp4	0.082	0.000	0.000	0.025	0.000	0.000	0.357	0.000

R Codes / Results for Generating the Centrality Indices for the Description and Inference Estimation of Edge-weights and their Accuracy:

1. Install boot net
2. Library(bootnet)
3. Network <- estimateNetwork(AERQ_37_ALL_Without_Outliers_and_Item_SocSup3,default = "EBICglasso")
4. Install qgraph
5. Library (qgraph)
6. plot(Network, layout = "spring",labels = TRUE)

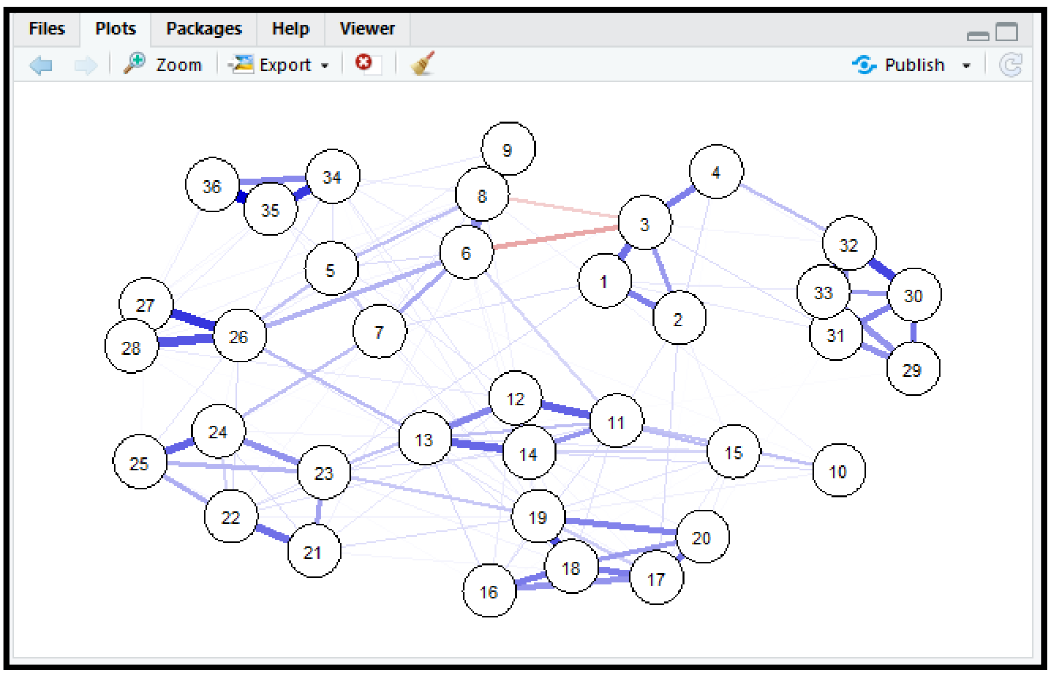


Figure 4.34 **Estimated Network Structure of AERQ. The network structure is a Gaussian graphical model, which is a network of partial correlation coefficients.**

Interpretation: The nodes 34,35 and36, 26,27 and 28, 11,12,13 and 14, 21 and 22, 24 and 25, 1,3 and 4, 6 and 8, 30 and 32 show strong connections among themselves. Red coloured edge-weights represent negative relationship shown between the nodes 3 and 6. Absence of edge-weights between nodes represents no relationship or orthogonality. For the remaining nodes, the edges are comparetively weak showing absence of sufficient power to find any relationship between them.

R Codes / Results for Obtaining Centrality Indices – Strength-wise

>centralityPlot(Network)

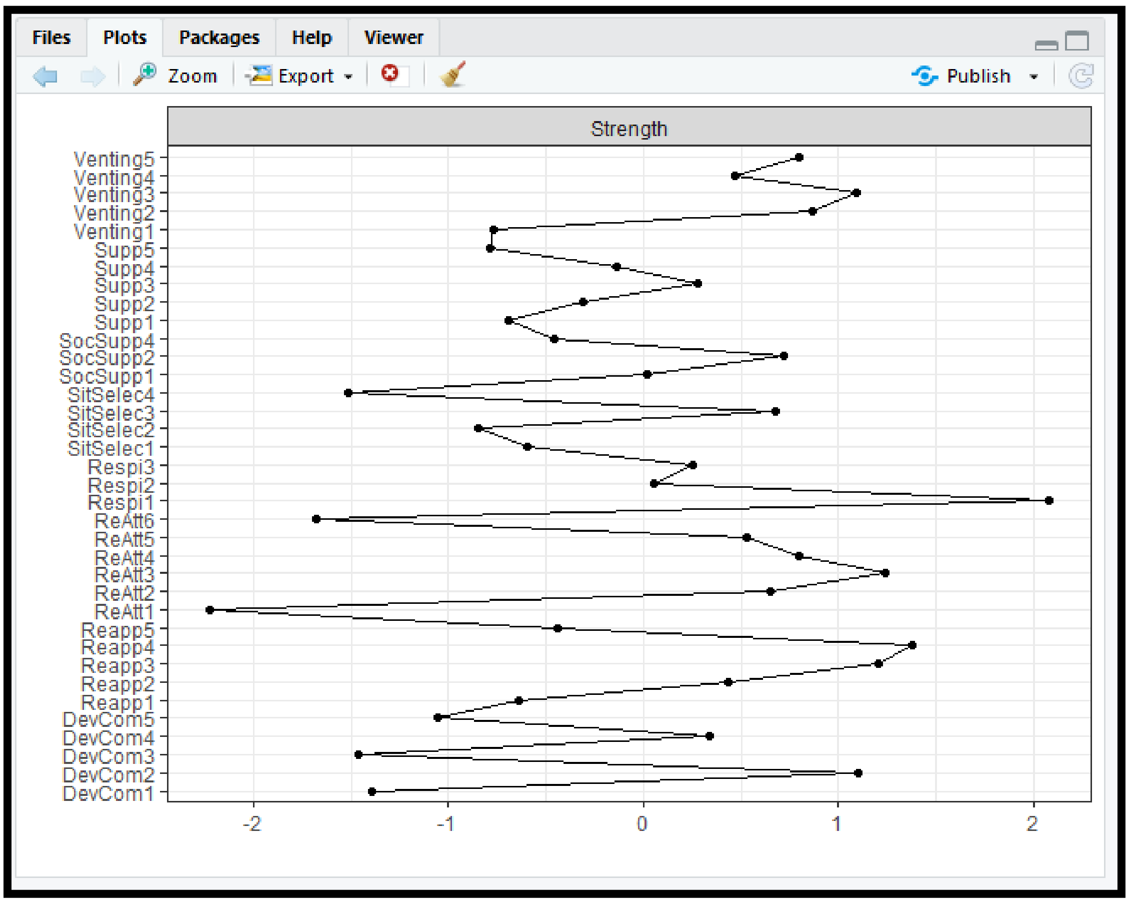


Figure 4.35 **Centrality Indices – Strength**

Interpretation: The strength of the nodes are varying in their magnitude with the node Respi2 having the highest strength and the strength of the node RA1 being the lowest.The next step is to check the significance in the order of the nodes with repect to their strength

R Codes / Results for Obtaining Edge weight Accuracy

boot1 <- bootnet(Network, nBoots = 100,nCores = 8)

```
plot(boot1, labels = FALSE, order = "sample")
```

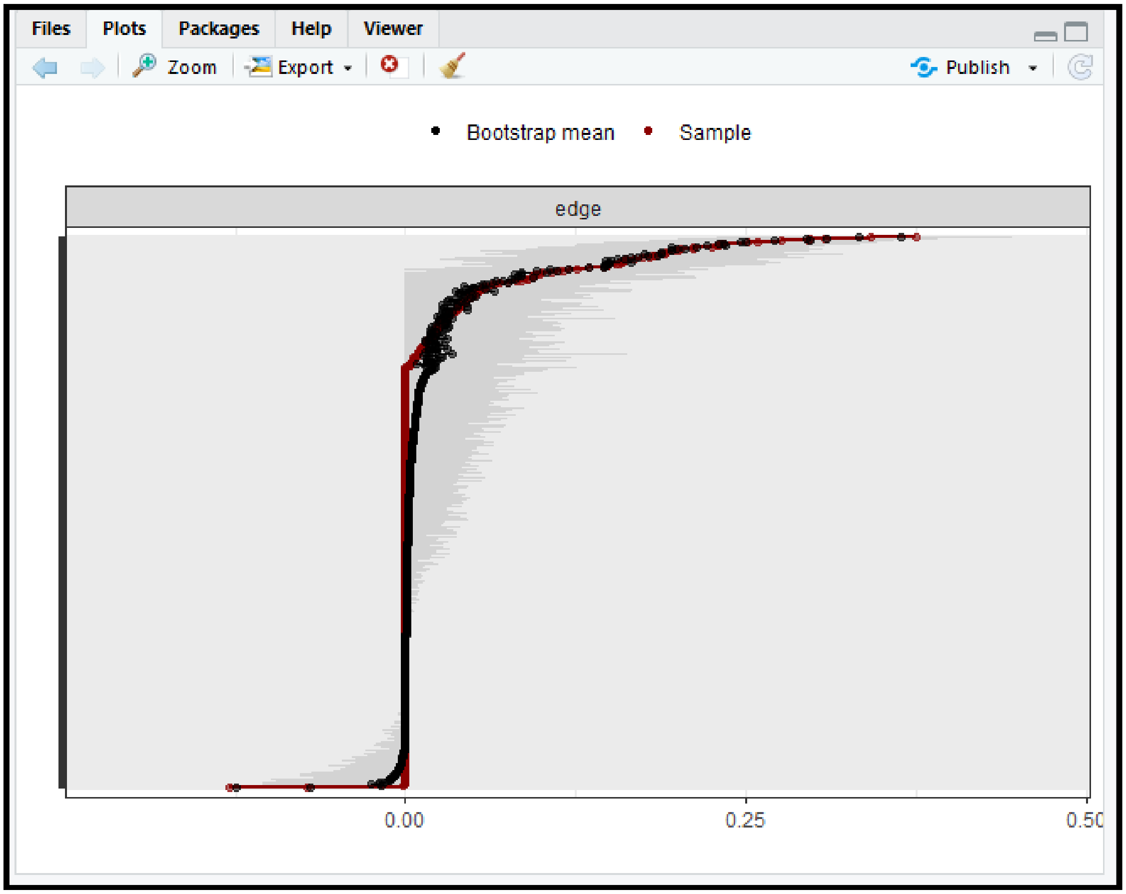


Figure 4.36 **Bootstrapped confidence interval of estimated edge-weights for the estimated network of AERQ.**

Interpretation: The significance in the order of the strength of the nodes is checked by computing the confidence interval and finding whether zero lies in that interval admist a negative abscissa and a positive ordinate. The red line indicates the sample values and the grey area the boot strapped CIs. Each horizontal line represents one edge of the network, ordered from the edge with the highest edge-weight to the edge with the lowest edge-weight.There is no significance difference when zero is present in the confidence interval. Significant difference results produce confidence interval out of boot strapping which do not contain zero. Here the nodes of AERQ show no significant difference in their node strength as the bootstrapped confidence interval contains zero(0, 0.5).

R Codes / Results for Obtaining Centrality Stability – CS Coefficient Estimation

boot2 <- bootnet(Network, nBoots = 100,type = "case", nCores = 8)

Plot(boot2)

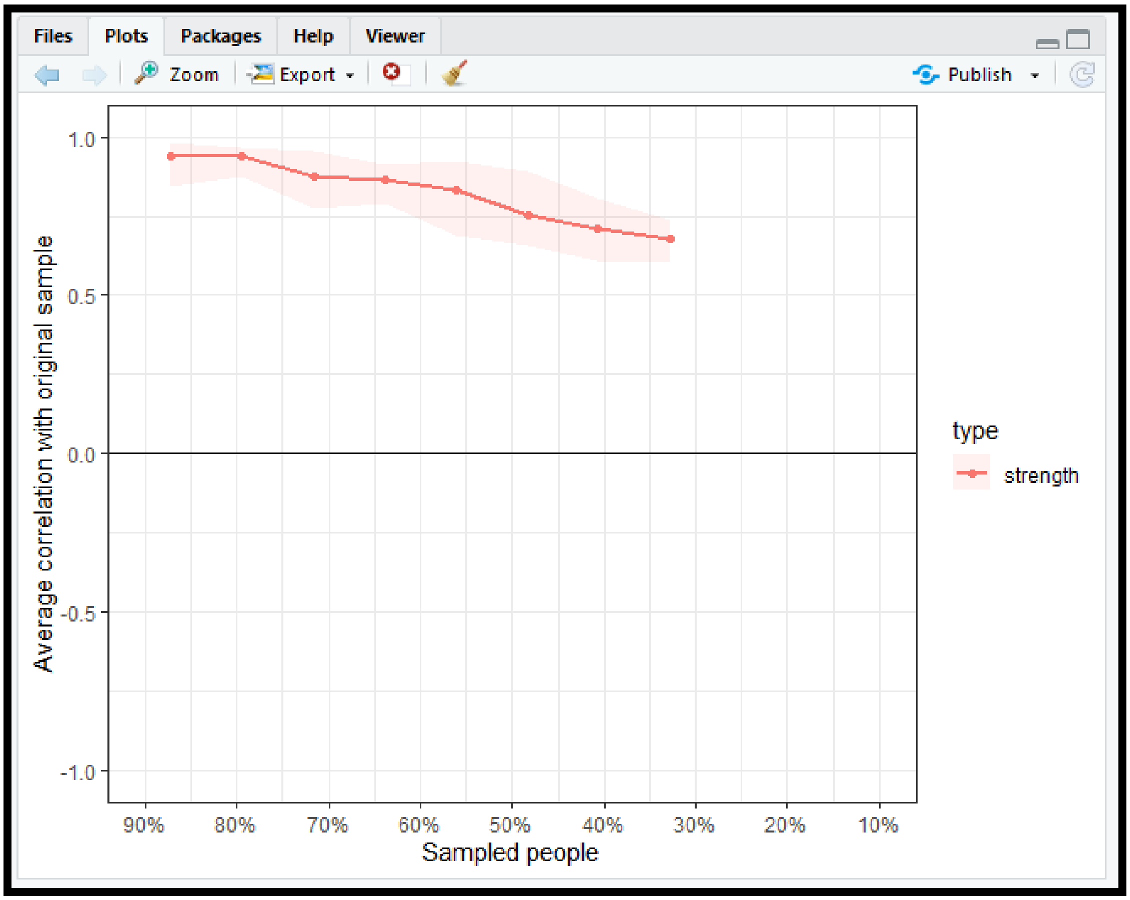


Figure 4.37 Average Correlation with Original Sample

corStability(boot2)

=== Correlation Stability Analysis ===

Sampling levels tested:
nPerson Drop% n
9 145 67.3 6

2	180	59.4	12
3	214	51.7	20
4	249	43.8	9
5	283	36.1	8
6	317	28.4	10
7	352	20.5	16
8	386	12.9	13
9	421	5.0	6

Maximum drop proportions to retain correlation of 0.7 in at least 95% of the samples:

edge: 0.673 (CS-coefficient is highest level tested)

- For more accuracy, run bootnet(…, caseMin = 0.594, caseMax = 1)

strength: 0.361

- For more accuracy, run bootnet(…, caseMin = 0.284, caseMax = 0.438)

Accuracy can also be increased by increasing both ‘nBoots’ and ‘caseN’.

Interpretation: The obtained the CS- coefficient of 0.673 is above the cutoff value of 0.5, which shows the reflection of good stability of items across multiple samples produced through 100 run of boot strapping. However, this stability falls quickly over the successive runs.

R Codes / Results for Conducting Pair-wise Significance Difference Test of Nodes:

differenceTest(boot1, 3, 17, "strength")

id1 id2 measure lower upper significant

1 SitSelec3 Reapp2 strength -0.3422148 0.3161339 FALSE

Interpretation: The test of significance difference between pairs of nodes, 3 and 17, that is first items of situation selection dimension and second item of Reappraisal dimension do not show any significant difference in the node strength centrality rightfully as they are items of different dimensions thorugh the result FALSE.

R Codes / Results for Estimating the Structural Consistency Reliability of each of the Dimensions of AERQ:

```
>library(haven)
>AERQFinal <- read_sav("D:/Ph.D/10. Ph.D. Article Publications and Paper Presentations/18. NP Based AERQ Validation/AERQFinal.sav")
>View(AERQFinal)
>ega.aerq<-EGA(AERQFinal, model = 'glasso')
>View(ega.aerq$dim.variables)
>net.loads(ega.aerq, ega.aerq$wc)$std
```

	1	2	3	4	5	6	7	8
DevCom1	0.128	0.000	0.000	0.057	0.017	0.031	0.004	0.000
DevCom2	0.300	-0.087	0.011	0.080	0.009	0.017	0.037	0.000
DevCom3	0.142	0.031	0.054	0.000	0.000	0.000	0.000	0.000
DevCom4	0.315	-0.048	0.008	0.036	0.000	0.016	0.023	0.000
DevCom5	0.236	0.000	0.000	0.020	0.000	0.021	0.000	0.000
SitSelec1	0.027	0.265	0.029	0.000	0.000	0.000	0.000	0.032
SitSelec2	0.000	0.261	0.000	0.000	0.028	0.000	0.030	0.000
SitSelec3	-0.119	0.366	0.000	0.000	0.000	0.000	0.000	0.033
SitSelec4	0.000	0.164	0.006	0.000	0.002	0.000	0.000	0.055
Supp1	0.012	0.000	0.239	0.000	0.033	0.000	0.018	0.000
Supp2	0.008	0.000	0.248	0.037	0.008	0.000	0.048	0.000
Supp3	0.000	0.033	0.251	0.006	0.052	0.000	0.068	0.000
Supp4	0.055	0.007	0.293	0.006	0.003	0.000	0.010	0.000
Supp5	0.000	0.000	0.268	0.030	0.000	0.000	0.002	0.000
Respi1	0.152	0.000	0.062	0.344	0.023	0.031	0.050	0.000
Respi2	0.007	0.000	0.003	0.402	0.000	0.024	0.000	0.000
Respi3	0.021	0.000	0.006	0.373	0.000	0.040	0.018	0.000
Reapp1	0.000	0.000	0.003	0.000	0.203	0.002	0.073	0.000
Reapp2	0.000	0.039	0.009	0.000	0.321	0.000	0.035	0.000
Reapp3	0.000	0.000	0.011	0.000	0.408	0.000	0.056	0.000
Reapp4	0.031	0.000	0.085	0.028	0.283	0.035	0.056	-0.001
Reapp5	0.000	0.000	0.000	0.000	0.276	0.000	0.023	0.003
SocSupp1	0.055	0.000	0.000	0.035	0.014	0.325	0.019	0.000
SocSupp2	0.018	0.000	0.000	0.029	0.013	0.464	0.026	0.000
SocSupp4	0.000	0.000	0.000	0.023	0.000	0.379	0.000	0.000
ReAtt1	0.018	0.000	0.000	0.000	0.011	0.000	0.087	0.000
ReAtt2	0.036	0.025	0.025	0.000	0.051	0.000	0.287	0.000
ReAtt3	0.008	0.000	0.069	0.020	0.044	0.027	0.323	0.000
ReAtt4	0.000	0.000	0.040	0.065	0.064	0.000	0.271	0.003
ReAtt5	0.013	0.000	0.031	0.000	0.024	0.034	0.311	0.000
ReAtt6	0.000	0.015	0.000	0.000	0.052	0.000	0.106	0.000
Venting1	0.000	0.000	0.000	0.000	0.000	0.000	0.003	0.262
Venting2	0.000	0.031	0.000	0.000	-0.001	0.000	0.000	0.409
Venting3	0.000	0.056	0.000	0.000	0.003	0.000	0.000	0.412
Venting4	0.000	0.073	0.000	0.000	0.000	0.000	0.000	0.337
Venting5	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.427

```
boot<- bootEGA(AERQFinal, n = 100, model = "glasso", type = "resampling", plot.typicalStructure = FALSE)
>sc<- dimStability(boot, orig.wc = ega.aerq$wc)
>sc$dimensions
1     2     3     4     5     6     7     8
0.910 0.902 0.906 0.680 0.738 0.960 0.932 1.000
```

Table 4.109 Structural Consistency Reliability of each Dimension of AERQ:

S.No.	Dimension	Items	Structural Consistency Reliability Estimate	Items displaying Structural Consistency
1.	Developing Competencies	5	0.910	4
2.	Situation Selection	4	0.902	4
3.	Suppression	5	0.906	4
4.	Respiration	3	0.68	2
5.	Reappraisal	5	0.738	4
6.	Social Support	3	0.96	3
7.	Redirecting Attention	6	0.932	5
8.	Venting	5	1.000	5

Interpretation: When boot strapping technique generates 100 non-parametric samples with the produced data, to check for the intactness of the five items of the dimension Venting, they are found to display consistency in their structure all along, measured by their structural consistency estimate of 1.000. Five items of the dimension Redirecting attention display structural consistency. This consistency estimate for the rest of the dimensions is also shown above. The dimension respiration shows the least structural consistency estimate in the AERQ scale implying that its items display a tendency of falling apart through cross-loading when searched in multiple boot strapped samples.

Conclusion: The AERQ scale was developed as a part of a Croatian research study on University students. The validity of the tool in a completely different foreign culture of

India tested through the state of the art Network Psychometrics analysis technique displays the amount of efforts placed by the researchers in the development of the tool initially. However, the tool needs further validation on larger samples, on subjects of different cultures and must undergo measurement invariance with respect to vital demographic variables like gender.

4.2.4 Validation of the Academic Intrinsic Motivation Scale in the Indian Context:
Vallerand et al. (1992) developed the academic motivation scale – AMS28, which is one of the widely used scales to measure the academic analogue of motivation among college students, based on the self determination theory by Deci and Ryan (1985,1991). The 28 items of the scale measures three types of intrinsic motivation, namely, "intrinsic motivation to know", "intrinsic motivation to accomplish things", "intrinsic motivation to experience stimulation", apart from three types of extrinsic motivation like "identified regulation", "introjected motivation", "external motivation" and amotivation (Vallerand, Blais, Briere and Pelletier, 1989).

According to Deci and Ryan (1985), intrinsic motivation is doing something for its very self and experiencing pleasure and satisfaction through mere participation in the act. Competence and self determination are the innate essence of intrinsic motivation. Intrinsic motivation to know is the doing an activity for experiencing the pleasure and satisfaction while doing, learning and comprehensing something new. Its counter part when creating or achieving something new, forms the instrinsic motivation towards accomplishments. When the mere engagement in an activity leads to experience of new stimulations, it forms the intrinsic motivation to experience stimulation.

The present study was conducted to validate the intrinsic motivation sub-scale of AMS-28, among engineering students of India. For this purpose, 282 students from IInd year of engineering from Lovely Professional University, Phagwara, Punjab and Osmania University, Hyderabad, Telangana were randomly selected. The tool was administered on them when the regular classes were in session and the students took 15-20 minutes to fill the tool and return it back to the researcher.

Since the factor structure was well established, its confirmation was sought through the technique of confirmatory factor analysis (CFA), which also validated the sub-scale, after estimating the descriptive statistics of the variables of interest. The reliability of the tool was reported using the polychoric ordinal alpha and ordinal omega along side the popular but erroneous Cronbach's alpha.

Table 4.110 Summary of Descriptive Statistics on the Scores of Academic Intrinsic Motivation:

The estimates of descriptive statistics, the measure of central tendency mean, the measure of dispersion standard deviation, the measures of asymmetry, skewness and kurtosis are reported along with their respective standard error.

Descriptive Statistics

	N	Mean	Std. Deviation	Skewness	Kurtosis
	Statistic	Statistic	Statistic	Statistic	Statistic
IMa2	282	4.794	1.753	-.436	-.676
IMa9	282	4.648	1.693	-.482	-.576
IMa16	282	4.737	1.625	-.586	-.237
IMa23	282	4.766	1.614	-.443	-.583
IMk3	282	4.602	1.714	-.413	-.611
IMk10	282	4.602	1.805	-.424	-.743
IMk17	282	4.684	1.641	-.364	-.776
IMK24	282	4.553	1.652	-.378	-.529
IMse1	282	3.985	2.087	.024	-1.293
IMse8	282	4.684	1.843	-.418	-.825
IMse15	282	4.652	1.949	-.368	-1.036
IMse22	282	4.542	1.731	-.346	-.677
Valid N (listwise)	282				

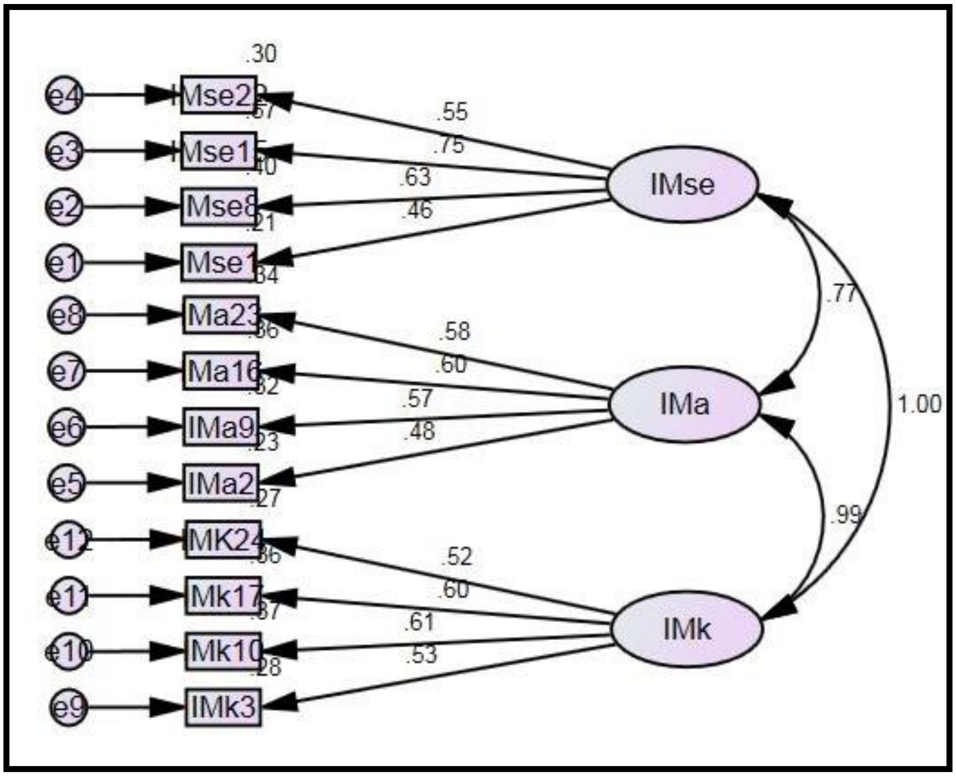


Figure 4.38 **Path Diagram of AIM**

The theoretical relationship between the three types of intrinsic motivation is evident through the graphical and statistical manifestation of the factor loadings of the items on each of the sub-scales in the above path diagram. The strength of the factor loadings ranges from being moderate to high, that is, from 0.46 to 0.75, which shows the effectiveness of the items in measuring their respective factor, along with strong inter-relationship between the dimensions of this type of intrinsic motivation.

Table 4.111Goodness of Fit Estimates of theAIM:

Estimate	p Value	CMIN/DF	RMR	RMSEA	GFI	IFI	TLI	CFI
Standards	>0.05	<3	<0.08	<0.08	>0.9	>0.9	>0.9	>0.9
Obtained Estimate	0.00	2.076	0.158	0.062	0.936	0.935	0.914	0.934

The maximum likelihood (ML) estimator is used to validate the factor structure of academic intrinsic motivation, confirmatory factor analysis, using SPSS AMOS Ver. 23.0

software. Barring RMR, remaining estimands of goodness of fit have acceptable estimates satisfying their desirable benchmark, confirming the validity of the factor structure of intrinsic academic motivation of AMS-28 in the Indian context.

Table 4.112 Reliability Analysis of AIM Scale:

S.No.	Dimension	Item	Cronbach's Alpha	Ordinal Alpha	Ordinal Omega
1.	IM_A	23	0.641	0.65	0.67
2.		16			
3.		9			
4.		2			
5.	IM_K	3	0.648	0.66	0.7
6.		10			
7.		17			
8.		24			
9.	IM_SE	1	0.691	0.72	0.76
10.		8			
11.		15			
12.		22			

Since the scale used to gather information is a seven point Likert scale, the responses are ordinal in nature and thus the true reliability of the sub-scales can be obtained by computing the polychoric alpha and omega reliability estimates. The procedure to follow in R/RStudio to compute the polychoric correlation matrix based ordinal alpha and ordinal omega are shown below:

1. Import the data file in RStudio console using *Import Dataset*.
2. Install the package *Psych*
3. Library *Psych* # for activation of the package#
4. Polychoric(datafilename)
5. Exampledata<-polychoric(datafilename)
6. Alpha(example$rho) # to estimate ordinal alpha
7. Omega(example$rho) # to estimate ordinal omega

All the three sub-scales under academic intrinsic motivation have acceptable reliability estimates, close to 0.7, equal to and above it. In this way, the items of the intrinsic academic motivation sub-scale of AMS-28 scale possess sufficient psychometric properties to measure this vital self regulated learning variable in the Indian context.

4.2.5 Validation of the Revised Academic Procrastination Scale Short Form in the Indian Context:

According to Moonaghi and Beydhokti (2017), academic procrastination is defined as “the tendency prevailed to postpone the academic activities and is almost always associated with anxiety.” It is the most common form of procrastination (Ferrari, 2001). Its relationship in the context of self regulated learning was established by Kandemir (2014). Instruments to measure this vital variable are rare in the Indian context and hence the present study adopted the 5 items shorter version of Academic Procrastination scale developed by Yockey (2016) which is taken from the 25 items full form of the scale developed by McCloskey (2011). The items taken from the original scale to form the shorter version are item number 2, 4,7, 17 and 23. The responses are recorded in a five-point Likert scale with 1=Agree and 5= Disagree. The Yockey’s scale displayed a convergent validity of with the most famous Tuckman’s scale of Procrastination and the Procrastination Assessment Scale – Student Version and reliability estimate Cronbach’s alpha of 0.87. Sopher (2019) calculator was used to conduct power analysis for level of significance 0.05, power 0.9, effect size 0.3, latent variable one and manifest variables 5. It provided a desired sample size of 100. The sample size of the present study was 105 from different schools of Lovely Professional University. The questionnaire of 9 students who did not fill the form properly was removed. It reduced the final sample size to 96 with 47 girls and 49 boys.

Table 4.113Revised Academic Procrastination Scale – Short Form - Tests of Normality

	Kolmogorov-Smirnov[a]	Shapiro-Wilk

	Statistic	Df	Sig.	Statistic	df	Sig.
I1	.225	96	.000	.844	96	.000
I2	.167	96	.000	.891	96	.000
I3	.164	96	.000	.884	96	.000
I4	.201	96	.000	.855	96	.000
I5	.147	96	.000	.903	96	.000

a. Lilliefors Significance Correction

The data gathered from the sample subjects on the five items of academic procrastination scale short form is skewed. It is because obtained statistics under Kolmogorov-Smirnov test and Shapiro Wilk test are significant and both these tests assume normality of the data under null hypothesis. A significant result reflects acceptance of alternate hypothesis which implies that the collected data is not normal.

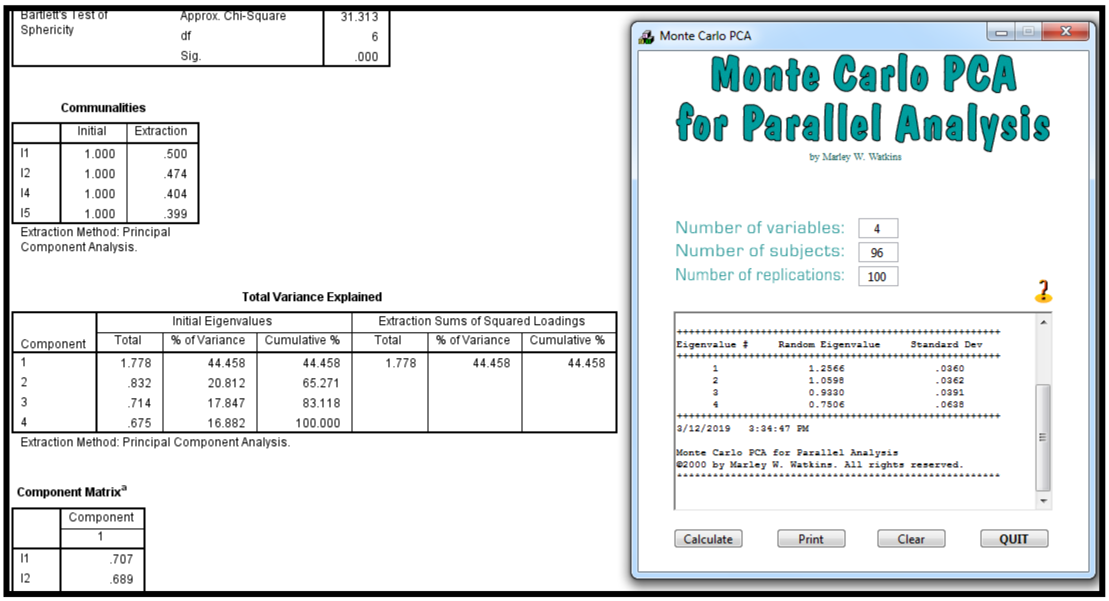
Table 4.114 Correlation Matrix[a]

		I1	I2	I3	I4	I5
Correlation	I1	1.000	.282	.043	.298	.265
	I2	.282	1.000	.126	.252	.280
	I3	.043	.126	1.000	.207	.076
	I4	.298	.252	.207	1.000	.176
	I5	.265	.280	.076	.176	1.000
Sig. (1-tailed)	I1		.003	.337	.002	.005
	I2	.003		.111	.007	.003
	I3	.337	.111		.022	.230
	I4	.002	.007	.022		.043
	I5	.005	.003	.230	.043	

a. Determinant = .677

When exploratory factor analysis (EFA) is conducted as per the above mentioned specifications, it resulted in a correlation matrix that clearly showed item 3 to be an odd entity in the instrument. Its correlation with rest of the items was weak and non-significant. The Kaiser-Meyer-Olkin KMO measure sampling adequacy was 0.676. When item 3 was deleted, and the EFA was conducted again, KMO revised to 0.683. The correlation matrix showed significant inter-relation between the four remaining items of the scale.

Barlett's test of sphericity was significant. The determinant is 0.714 which is way above the limit of 0.00001. The varimax rotation extracted one factor which explained 44.458% of variance in the construct. The obtained eigen value from the rotation exercise was 1.778.



Bartlett's Test of Sphericity	Approx. Chi-Square	31.313
	df	6
	Sig.	.000

Communalities

	Initial	Extraction
I1	1.000	.500
I2	1.000	.474
I4	1.000	.404
I5	1.000	.399

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1.778	44.458	44.458	1.778	44.458	44.458
2	.832	20.812	65.271			
3	.714	17.847	83.118			
4	.675	16.882	100.000			

Extraction Method: Principal Component Analysis.

Component Matrix[a]

	Component
	1
I1	.707
I2	.689

Figure 4.39 **The proof of unidimensionality of Revised Academic Procrastination – Short Form**

When MonteCarlo Parallel analysis was run for number of variables 4, number of subjects 96 and for 100 iterations, it provided a critical eigen value of 1.2566 which was less than the obtained eigen value of 1.778 from EFA. This clearly showed that the construct is unidimensional here. The descriptive statistics of the retained four items are shown in the table below:

Table 4.115 Summary of Descriptive Statistics on the Scores of Revised Academic Procrastination

	N	Minimum	Maximum	Mean	Std. Deviation	Variance	Skewness	Kurtosis
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic
I1	96	1.00	5.00	2.3333	1.31922	1.740	.736	-.568
I2	96	1.00	5.00	3.1979	1.35040	1.824	-.055	-1.229
I4	96	1.00	5.00	3.2708	1.48309	2.200	-.144	-1.450
I5	96	1.00	5.00	2.9688	1.32548	1.757	.031	-1.053
Valid N (listwise)	96							

In the next stage of the study, confirmatory factor analysis was conducted using SPSS AMOS ver.23 software. It provided the factor loadings of the items 1, 2, 4 and 5 as shown in the figure and the table below:

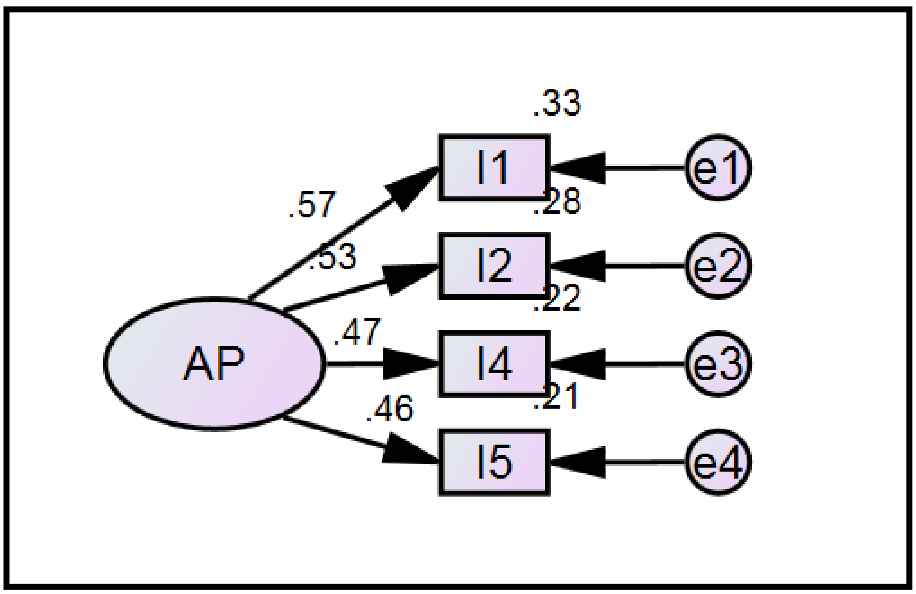


Figure 4.40**Factor Loadings of 4 Items on APS-SF**

Table 4.116 Items-Factor Loading – APS- SF

Item	Factor Loading
1	0.57
2	0.53
4	0.47
5	0.46

The GFI is 0.996. The IFI is 1.043. The TLI value was 1.148. The value of TLI need not be between 0 and 1 (Schermelleh-Engel and Moosbrugger, 2003; Ding et al., 1995; Gerbing and Anderson, 1992). The CFI value was 1.000. The cut-off value of all the measures of goodness of fit is 0.93 (Hu and Bentler, 1999). These evidences confirm the single-factor structure of the revised academic procrastination scale post purification in the Indian context and establish the construct validity of the instrument.

Table 4.117 Goodness of Fit Measures – Unconstrained Structure

Measure	P value	CMIN/DF	RMR	RMSEA	GFI	IFI	TLI	CFI
Benchmark	>0.05	< 3	<0.08	<0.08	>0.93	>0.93	>0.93	>0.93
Result	0.698	0.359	0.039	0.000	0.996	1.043	1.148	1.000

Table 4.118 Goodness of Fit Measure – Configural Measurement Invariance Testing: Constrained Structure – Gender

Measure	P Value	CMIN/ DF	RMR	RMSEA	GFI	IFI	TLI	CFI
Benchmark	>0.05	<3	<0.08	<0.08	>0.93	>0.93	>0.93	>0.93
Result	0.699	0.550	0.075	0.000	0.989	1.042	1.153	1.000

The chi-square and df value for the unconstrained structure were 0.7 and 2 respectively. For evaluating configural invariance of the revised model, it is constrained by making two groups of boys and girls and keeping the regression weight of both the groups same. The chi-square and df values for the constrained structure were 2.2 and 4 respectively. When the difference of these values was calculated, it was found that the p-value was 0.472 (> 0.05), which means that the factor structure of revised academic procrastination scale is invariant with respect to gender, or the scale is configural invariant. For testing metric invariance, the variance of the two groups was kept the same. The scale was found to be metric variant as the p-value for the next hierarchical structure was found to be 0.018 (< 0.05). It means that boys and girls interpret the meaning of the four items of the revised scale differently. Further studies of invariance are hence halted here.

Estimation of Greatest Lower Bound Reliability:

Cronbach's alpha as a measure of internal consistency reliability can be reported only when the condition of Tau-equivalence is not violated (Cronbach, 1951). Under this condition, Cronbach's alpha is the measure of internal consistency reliability of the items, only when these items not only load on a single construct but also with equal factor loading. Also, the data distribution should be normal (Green and Yang, 2009). In the case of violation of Tau-equivalence condition but existence of normality of the data, Raykov's composite reliability can be reported as the measure of reliability (Raykov, 1997). However, in all realistic conditions, neither the factor loadings of all the items are exactly equal nor the data is normal. In such a situation, the Cronbach's alpha should be abandoned (Green & Thompson, 2005, Graham, 2006; Peters, 2014). Usage of Cronbach's alpha even under the violation of Tau-equivalance leads to the underestimation of the actual reliability of the scale ranging from 0.6 to 11 percent on the basis of the gravity of the violation (Raykov, 1997). In such a case, the reporting of a less known but the powerful confidence interval estimator of reliability known as the greatest lower bound or GLB should be reported (Woodhouse and Jackson,1977). From its very definition, the GLB of scale lies between confidence interval (GLB,1).

In the present study, the FACTOR software (Lorenzo-Seva and Ferrando, 2006, 2013) was used to calculate this psychometric property and found to be in between (0.622,1), which is acceptable for psychological instruments (Kline, 1999). It means that the true reliability of the revised scale for the selected sample subjects, lies anywhere between the minimum value of 0.622 and the maximum value of 1, for sure.

The parsimonious version of academic procrastination scale short form by Yockey (2016) is validated in the Indian context along with the testing of its measurement invariance. The scale is configural invariant which implies that the factor structure of the four items of the parsimonious version of this tool is invariant across boys and girls. However, it is metric variant. The tools' true reliability lies between 0.622 and 1. Hence, the tool stands validated in the Indian context.

4.2.6 Validation of the Zimbardo Time Perspective Inventory Short Form in the Indian Context:

According to Nuttin (1964) and Zimbardo and Boyd (1999), Time perspective (TP) is defined as "the process using which individuals separate the passing of their personal experiences into mental time periods involving the past, the present and the future". Multiple areas of life and health are affected by this vital construct and its factors (Guthrie et al.2009; Adams andWhite 2009; Carstensen and Fredrickson 1998; Hall and Fong 2003; Rothspan and Read 1996), self-esteem (Worrell and Mello 2009), identity formation, coping (Wills et al. 2001; Beiser and Hyman 1997), stress perception (Worrell and Mello 2009; Zimbardo and Boyd 1999) anduse of substance (Keough et al. 1999; Wills et al. 2001).

The 56 items Zimbardo Time Perspective Inventory (Zimbardo and Boyd, 1999) is the most commonly used instrument to measure time perspective. It has five dimensions, "Future (F), Present Fatalistic (PF), Present Hedonistic (PH), Past Positive (PP) and Past Negative (PN)", whose structure is validated in multiple countries across the world (Sircova et al., 2014) with the notoriety of its factor structure getting revealed from time to time (Crockett et al., 2009;Perry et al., 2015). As a result, an exercise of developing parsimonious versions of this scale was initiated (Temple et al., 2017). The 20 items Hebrew version (Orkibi, 2015), the 15 items Czech and Slovak version (Kost et al., 2016) and the 17 items Hungarian version (Orosz et al., 2017) are the three recently developed short scales of time perspective. Since the Hungarian version is the latest and retains the original five factors of the construct, it was chosen for validation and adaptation in the Indian context in this study. There are 17 items in the Hungarian version with the responses recorded as "Very Uncharecteristic = 1" to "Very Characteristic = 5" on a five point Likert scale.

Table 4.119 Items Retained Per Factor in the Hungarian Version from the Original 56 Items Zimbardo and Boyd (1999):

S.No.	Dimension	Items Retained from the Original Version
1.	Past Negative	Items (22, 25, 34, 50)
2.	Present Hedonism	Items (31, 42, 46)
3.	Past Positive	Items (15, 20, 29)
4.	Future	Items (13, 21, 40, 45)
5.	Present Fatalism	Items (37, 38, 39)
Psychometric Properties during the Validation Study: Good model fit indices (CMIN/DF=3.22, RMSEA – 0.04, CFI = 0. 953, TLI = 0.941 and SRMR = 0.039) and internal consistency reliability (0.68 – 0.73).		

The sample of the present study comprised of 215 engineering students of computer science stream from the School of Computer Science and Engineering, Lovely Professional University, Pahgwara, Punjab, India. There were 28 outliers, on whose removal the total sample size reduced to 187 participants with 28 girls and 159 boys, whose average age was 19 years and selected using simple random sampling technique. After receiving the permission of administration of the test from the concerned authorities, the data was collected during the regular class session. Post instructions, the students took 15-20 minutes to fill and return the tool to the researcher.

Results:

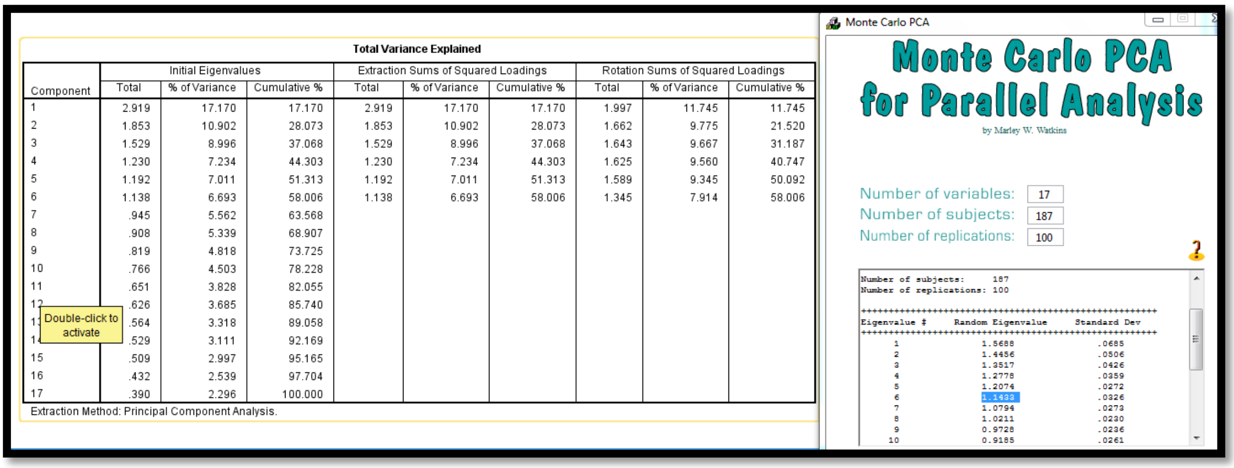
Table 4.120 Descriptive Statistics of the 16 Items of Time Perspective Scale

	Mean	Std. Deviation	Analysis N
ZTP1	3.3155	1.01702	187
ZTP2	3.3262	1.10983	187
ZTP3	3.2620	1.20072	187
ZTP4	2.9947	1.18457	187
ZTP5	3.4652	1.25836	187
ZTP6	3.4599	1.27095	187
ZTP7	3.3957	.98569	187
ZTP8	3.8770	.95650	187

ZTP9	3.4064	1.10986	187
ZTP10	3.9412	.96262	187
ZTP12	3.2139	1.23010	187
ZTP13	3.4652	1.08391	187
ZTP14	3.4706	1.00158	187
ZTP15	3.3529	1.25875	187
ZTP16	2.6310	1.15828	187
ZTP17	2.7914	1.25909	187

Exploratory Factor Analysis:

As a part of preparation for exploratory factor analysis, the form of extraction chosen was Principal component analysisalong with varimax rotation method and coefficient absolute value of 0.32.The data was found to be worthy of exploratory factor analysis as the determinant obtained was 0.077 well above the cut off value of 0.00001. The sample size of the study was adequate as the KMO sampling adequacy was 0.658 and just above the cut off value of 0.6. The correlation matrix was worthy of analysis since the significant result of Barlett's test of sphericity was obtained. The EFA extracted six factors through SPSS Statistics software Ver. 23. Hong's Parallel analysis test using Monte Carlo PCA software was further conducted to confirm the number of factors with the eigen values of the generated factors by SPSS being greater than the first six critical eigen values generated by Parallel analysis software



Total Variance Explained

Component	Initial Eigenvalues Total	% of Variance	Cumulative %	Extraction Sums of Squared Loadings Total	% of Variance	Cumulative %	Rotation Sums of Squared Loadings Total	% of Variance	Cumulative %
1	2.919	17.170	17.170	2.919	17.170	17.170	1.997	11.745	11.745
2	1.853	10.902	28.073	1.853	10.902	28.073	1.662	9.775	21.520
3	1.529	8.996	37.068	1.529	8.996	37.068	1.643	9.667	31.187
4	1.230	7.234	44.303	1.230	7.234	44.303	1.625	9.560	40.747
5	1.192	7.011	51.313	1.192	7.011	51.313	1.589	9.345	50.092
6	1.138	6.693	58.006	1.138	6.693	58.006	1.345	7.914	58.006
7	.945	5.562	63.568						
8	.908	5.339	68.907						
9	.819	4.818	73.725						
10	.766	4.503	78.228						
11	.651	3.828	82.055						
12	.626	3.685	85.740						
1[illegible]	.564	3.318	89.058						
1[illegible]	.529	3.111	92.169						
15	.509	2.997	95.165						
16	.432	2.539	97.704						
17	.390	2.296	100.000						

Extraction Method: Principal Component Analysis.

Number of subjects: 187
Number of replications: 100

Eigenvalue #	Random Eigenvalue	Standard Dev
1	1.5688	.0685
2	1.4456	.0506
3	1.3517	.0426
4	1.2778	.0359
5	1.2074	.0272
6	1.1433	.0326
7	1.0794	.0273
8	1.0211	.0230
9	0.9728	.0236
10	0.9185	.0261

Figure 4.41 **Hong's Parallel Analysis for Factor Extraction of Time Perspective Scale**

Table 4.121 Rotated Component Matrix[a]

	Component					
	1	2	3	4	5	6
ZTP13	.763					
ZTP12	.724					
ZTP14	.580					
ZTP8	.498	.453				
ZTP11		.763				
ZTP10		.596				.396
ZTP6			.726			
ZTP5			.673			
ZTP7			.544		.410	
ZTP3				.763		
ZTP1				.583		
ZTP4				.561		
ZTP15					.694	
ZTP9		.333			.663	
ZTP2				.450	.648	
ZTP16						.789
ZTP17			.384			.522

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.[a]
a. Rotation converged in 10 iterations.

Since the first run of EFA, item 11 displayed split loading, it was eliminated. In the second run, Principal component analysis, but with Quartimax rotation, was administered to arrive at the number of factors close to the theoretically indicated five factors. Quartimax rotation is the opposite of varimax rotation. In Quartimax rotation, the number of factors required for explaining the reflecting variables are kept low, allowing easy interpretation of the items. In varimax rotation, the items having very high factor loading on every dimension is kept low, which allows easyinterpretation of the dimensions. Five factors as indicated by the theory was obtained in the second run with determinant 0.077, KMO sampling adequacy 0.658, significant Barlett’s test of sphericity and the extracted explaining 51.313 percent of the variance in time perspective. Hong’s parallel analysis confirmed the five factors extraction as well, as the obtained eigen values were greater for the first five critical eigen values.

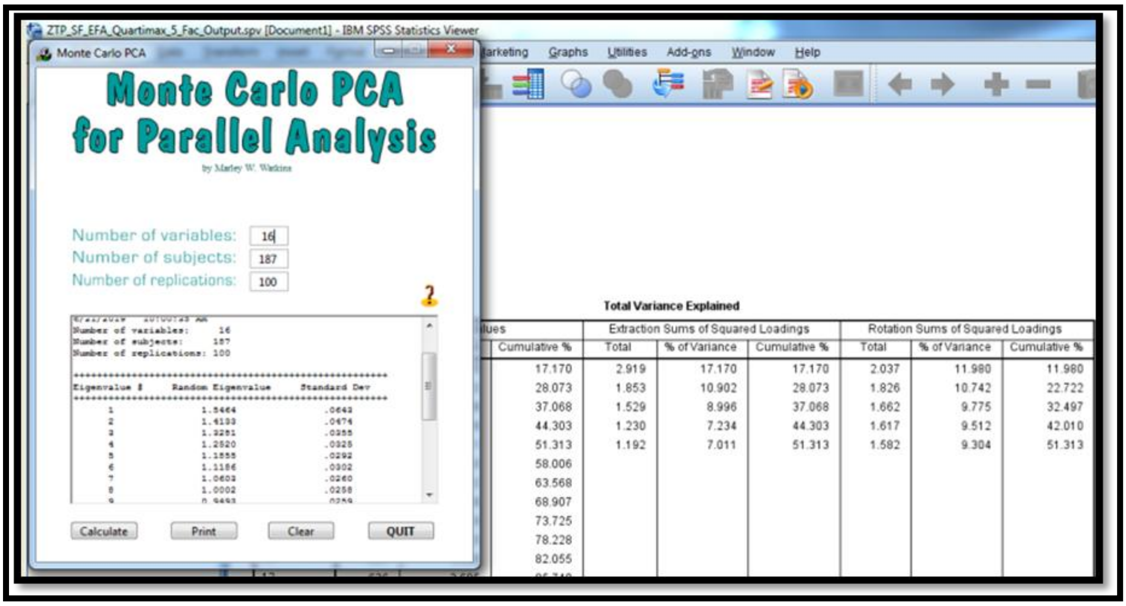


Figure 4.42 **Hong Parallel Analysis**

Table 4.122 Comparision of the Critical and Obtained Eigen Values

Fa.No.	Critical Eigen Value	Obtained Eigen Value
1.	1.5464	2.037
2.	1.4133	1.826
3.	1.3281	1.662
4.	1.2520	1.617
5.	1.1855	1.582

Table 4.123 Reliability Statistics

Cronbach's Alpha	N of Items
.663	16

According to Cortina (1993), the internal consistency reliability using Cronbach's alpha is less for scales with more number of factors and less number of items loading on them. The 16 items display the Cronbach's alpha of 0.663 which is acceptable according to Kline (1999).

Table 4.124Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
ZTP1	.205	187	.000	.903	187	.000
ZTP2	.236	187	.000	.895	187	.000
ZTP3	.207	187	.000	.905	187	.000
ZTP4	.163	187	.000	.915	187	.000
ZTP5	.226	187	.000	.885	187	.000
ZTP6	.237	187	.000	.880	187	.000
ZTP7	.205	187	.000	.890	187	.000
ZTP8	.284	187	.000	.836	187	.000
ZTP9	.226	187	.000	.890	187	.000
ZTP10	.214	187	.000	.855	187	.000
ZTP12	.182	187	.000	.909	187	.000
ZTP13	.240	187	.000	.893	187	.000
ZTP14	.252	187	.000	.881	187	.000
ZTP15	.156	187	.000	.899	187	.000
ZTP16	.220	187	.000	.902	187	.000
ZTP17	.195	187	.000	.905	187	.000

a. Lilliefors Significance Correction

Neither the data is normal, nor are the condictions of tau-equivalence satisfied. The Cronbach's alpha underestimates the true reliability of scales under such circumstances and hence alternative estimates of reliability like the greatest lower bound reliability must be reported. The GLB of the present 16 items of ZTPI short form found using FACTOR software was found to be (0.822,1). Hence, there is an underestimation of at least 19 percent of the true reliability of the scale by Cronbach's alpha in this study.To confirm the stability of the factor structure, the confirmatory factor analysis test is conducted using SPSS AMOS Ver. 23.0 with the following results:

Confirmatory Factor Analysis:

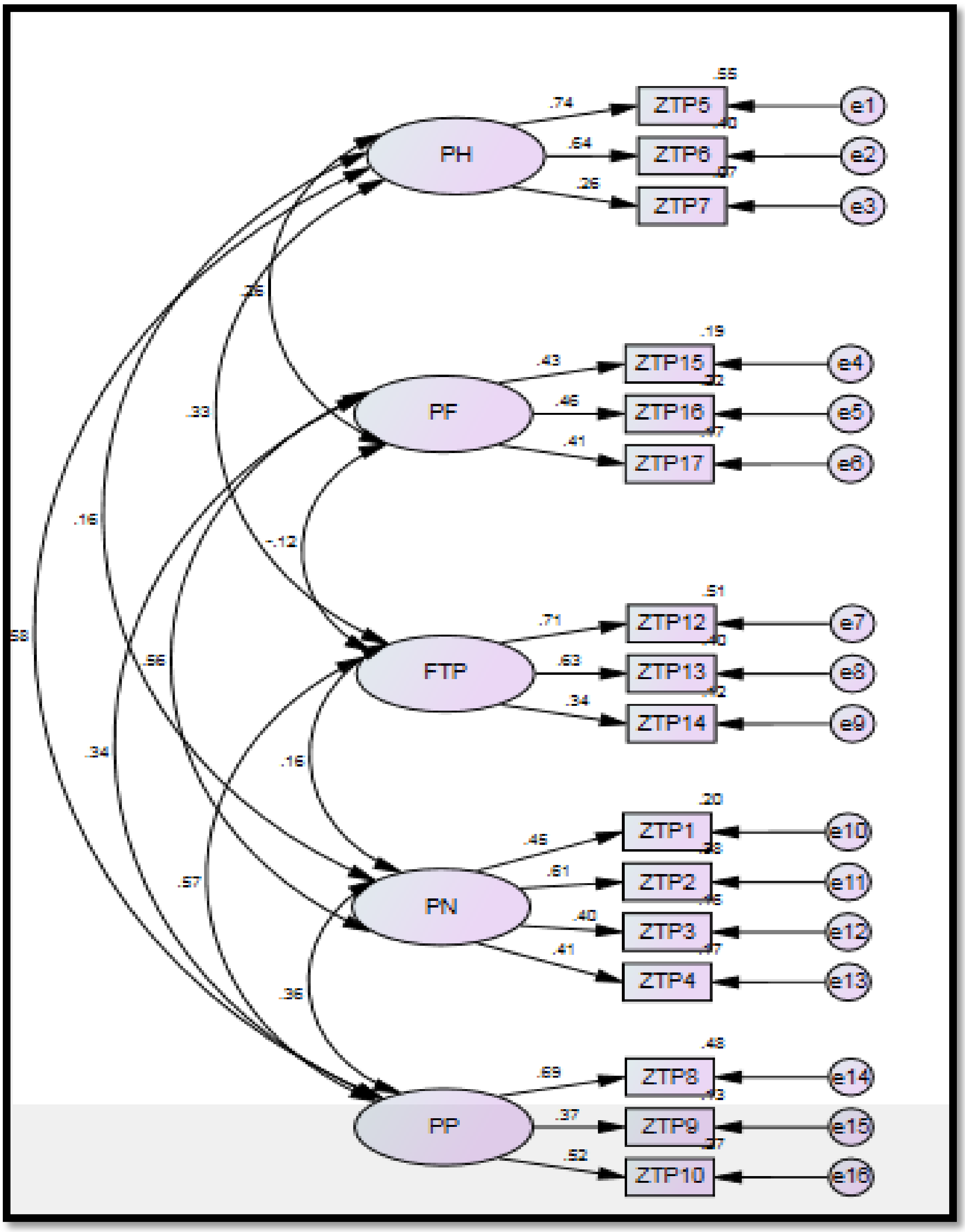


Figure 4.43 **Factor Structure of ZTPI – SF in the Indian Context:**

The estimates of the path diagram show that the items measuring their respective factors are closely associated with them. Their intact is confirmed through the estimates of goodness of fit as shown below:

Table 4.125Goodness of Fit Estimates of ZTPI-SF:

Estimate	CMIN/DF	IFI	TLI	CFI	RMSEA
Benchmark	< 3.00	> 0.9	> 0.9	> 0.9	< 0.08
Result	1.360	0.899	0.86	0.891	0.044

The CMIN/DF is 1.360 is acceptable since it is very less than 3.00 as desired. The incremental fit index (IFI) is 0.899 which is same as its benchmark of 0.9. Also, the Tucker-Lewis index (TLI) and Comparative Fit Index (CFI) estimates are 0.86 and 0.891, almost near to the benchmark of 0.9. The root mean square error of approximation RMSEA estimate at 0.044 is very acceptable as it is desirably less than its benchmark of 0.08 (Hu and Bentler, 1999). The above obtained evidences validate the parsimonious version of time perspective scale in the Indian context.

Table 4.126Status of the Items from ZTPI – SF (2017) Scale on Adoption in Indian Context:

Item No.	Item Statement	Status
1	"I have taken my share of abuse and rejection in the past"	Retained
2	"I think about the bad things that happened to me in the past"	Retained
3	"The past has too many unpleasant memories that I prefer not to think about"	Retained
4	"It is hard for me to forget unpleasant images of my youth"	Retained
5	"I take risks to put excitement in my life".	Retained
6	"Taking risks keeps my life from becoming boring."	Retained
7	"I find myself getting swept up in the excitement of the moment."	Retained
8	"Happy memories of good times spring readily to mind.	Retained
9	"I get nostaligic about my childhood."	Retained
10	"I enjoy stories about how things used to be in the "good old times"."	Retained
11	"Meeting tomorrow's deadline and doing other necessary work come before tonight's play"	***Removed***
12	"I complete projects on time by making steady progress."	Retained
13	"I am able to resist temptation when I know that there is work to be done."	Retained
14	"I meet my obligations to friends and authorities on time."	Retained
15	"You can't really plan for the future because things change so much."	Retained

16	"My life path is controlled by forces I cannot influence."	Retained
17	does not make sense to worry about the future, since there is nothing that I can do about it anyway."	Retained

4.2.7 Validation of the Parsimonious Academic Delay of Gratification Scale:

The academic delay of gratification scale developed by Bembenutty and Karabenick (1996) is a gold standard in the measurement of the academic analogue of delay of gratification. The tool was validated in the Indian context and shown to be configural invariant across gender in the Indian context by the researcher (Chakraborty, 2017). The present study was conducted to come up with a parsimonious version of the sam tool. 187 students (159 boys and 28 girls) of IInd year from"School of Computer Science and Engineering, Lovely Professional University", Phagwara, Punjab, India were sample of this study. The tool was administered when a regular class was in session.

Table 4.127 Descriptive Statistics of the Parsimonious Academic Delay of Gratification Scale:

	N	Mean	Std. Deviation	Skewness	Kurtosis
	Statistic	Statistic	Statistic	Statistic	Statistic
ADGS1	187	2.604	1.028	-.044	-1.031
ADGS2	187	2.262	1.011	.211	-1.085
ADGS3	187	2.427	1.116	.078	-1.350
ADGS4	187	2.951	1.063	-.607	-.908
ADGS5	187	2.604	1.069	-.168	-1.208
ADGS6	187	2.481	1.137	-.009	-1.404
ADGS7	187	2.385	1.047	.167	-1.154
ADGS8	187	3.053	.982	-.658	-.702
ADGS9	187	2.524	1.043	-.036	-1.170
ADGS10	187	2.807	1.013	-.388	-.955
Valid N (listwise)	187				

The reliability of the scale with the 10 items is just acceptable at 0.598 or 0.6 according to Kline (1999). The stability of the factor structure is estimated using confirmatory factor analysis through SPSS AMOS Ver.23.0, with the following factor loadings on the path diagram and goodness of fit estimates:

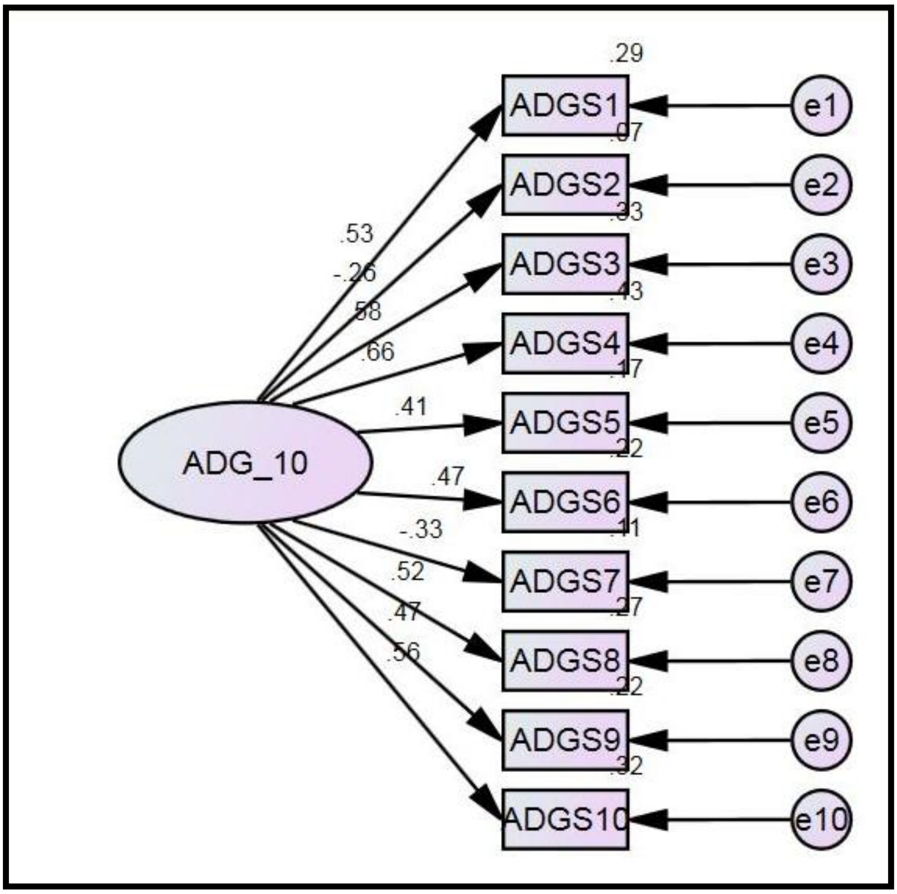


Figure 4.44 **Path Diagram of Academic Delay of Gratification – Original Scale**

Table 4.128Goodness of Fit Estimates – Original ADGS :

Estimate	**CMIN/DF**	**IFI**	**TLI**	**CFI**	**RMSEA**	**AIC**	**BIC**
Benchmark	< 3.00	> 0.9	> 0.9	> 0.9	< 0.08	Default model	Default model
Result	3.161	0.771	0.618	0.757	0.107	179.62	174.37

In order to obtain a better fit, items with factor loadings over 0.5 were selected and subjected to confirmatory factor analysis. The reliability estimate found by the calculation of Cronbach's alpha was found to be at 0.71.

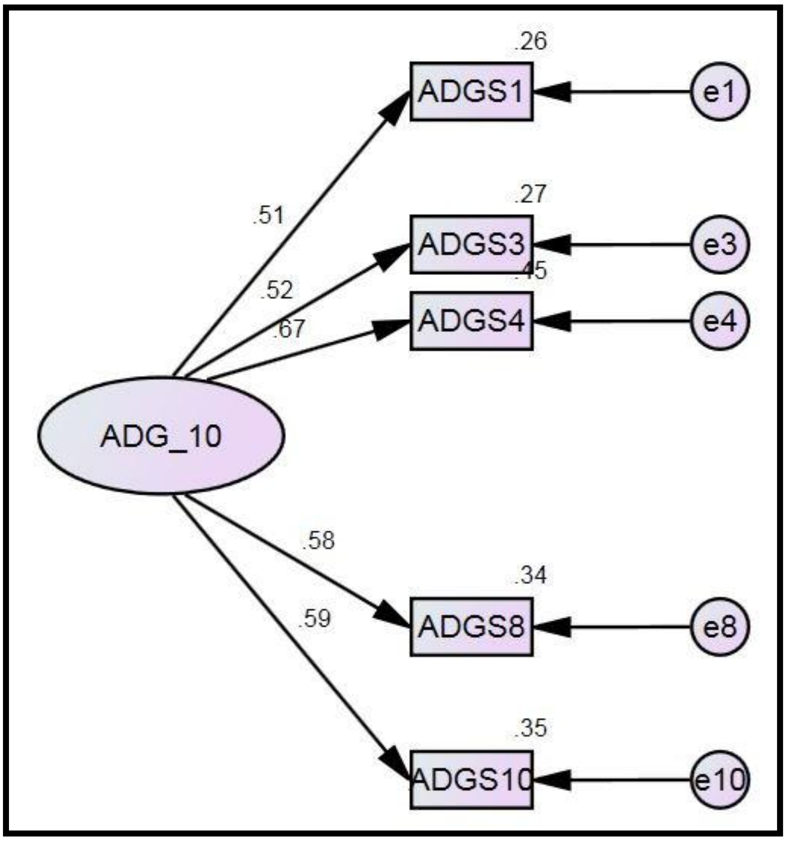


Figure 4.45 **Path diagram of the Parsimonious Academic Delay of Gratification Scale**

Table 4.129Goodness of Fit Estimates – First Parsimonious ADGS:

Estimate	**CMIN/DF**	**IFI**	**TLI**	**CFI**	**RMSEA**	**AIC**	**BIC**
Benchmark	< 3.00	> 0.9	> 0.9	> 0.9	< 0.08	179.62	174.37
Result	2.517	0.95	0.841	0.947	0.09	42.587	43.582

According to Geiser (2011), the parsimonious model with five items, namely item 1,3,4,8 and 10, forms a better model owing to its lower BIC value. Moreover, there is improvement in the goodness of fit estimates with CMIN/DF and CFI satisfying the respective benchmark.

In order to search for a better parsimonious model, the factor loadings of the remaining items of the original scale were searched. A second model was formed with items 4, 5, 8, 9 and 10. The Cronbach's alpha was found to be at 0.692 lesser than the first parsimonious model. Its path diagram is shown below:

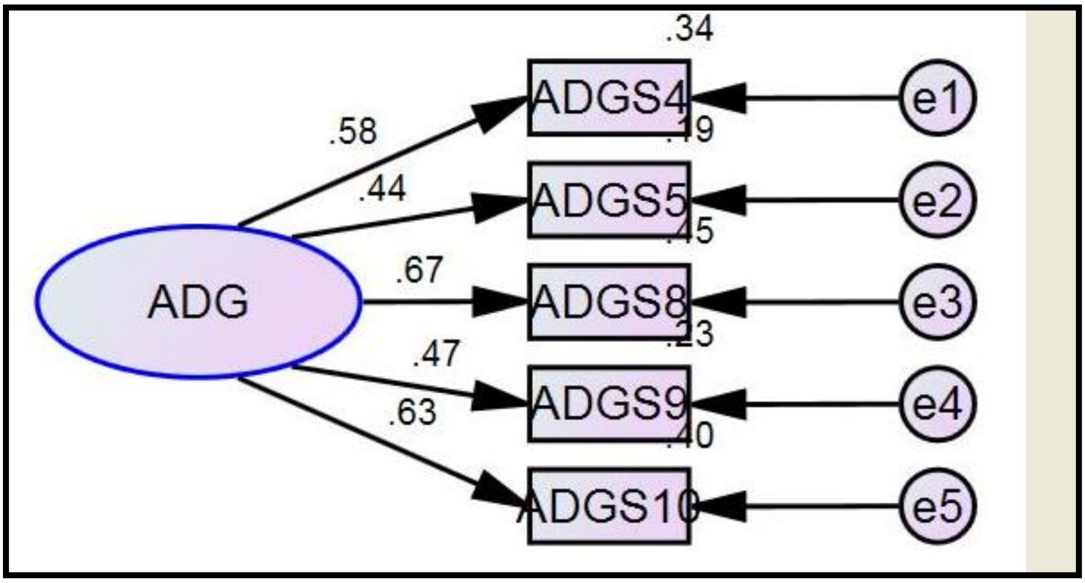


***Figure 4.46*Path diagram of the Final Parsimonious Academic Delay of Gratification Scale**

Table 4.130Goodness of Fit Estimates - Second Parsimonious ADGS:

Estimate	**CMIN/DF**	**IFI**	**TLI**	**CFI**	**RMSEA**	**AIC**	**BIC**
Benchmark	< 3.00	> 0.9	> 0.9	> 0.9	< 0.08	42.587	43.582
Result	2.099	0.961	0.875	0.958	0.077	40.497	41.491

The second model is not only a better model with respect to parsimony with lesser BIC value but also has finer goodness of fit estimates through the satisfaction of the benchmarks of all the estimates except TLI. Ultimately, in the light of these evidences, the second model of parsimony of academic delay of gratification is considered in this study.

4.2.8 Validation of the Volition Component of the Self Regulated Learning in the Indian Context:

187 students (159 boys and 28 girls) of IInd year from "School of Computer Science and Engineering, Lovely Professional University", Phagwara, Punjab, India were sample of this study. The tools administered when a regular class was in session, were the parsimonious versions of academic delay of gratification scale, academic procrastination scale and the Zimbardo time perspective scale. The results of the study were as follows:

Table 4.131 Descriptive Statistics of the Volition Component of the Self Regulated Learning:

	N	Mean	Std. Deviation	Skewness	Kurtosis
.	Statistic	Statistic	Statistic	Statistic	Statistic
ZTP12	187	3.213	1.230	-.223	-.891
ZTP13	187	3.465	1.083	-.499	-.378
ZTP14	187	3.470	1.001	-.600	.061
APS1	187	3.203	1.328	-.226	-1.149
APS2	187	2.967	1.315	.088	-1.067
APS3	187	3.283	1.359	-.358	-1.088
APS4	187	2.909	1.428	.038	-1.387
ADGS4	187	2.951	1.063	-.607	-.908
ADGS5	187	2.604	1.069	-.168	-1.208
ADGS8	187	3.053	.982	-.658	-.702
ADGS9	187	2.524	1.043	-.036	-1.170
ADGS10	187	2.807	1.013	-.388	-.955
Valid N (listwise)	187				

Table 4.132: Reliability Analysis of Volition Variables:

S.No.	Name of the Variable	Item No	Cronbach's α	Guttman's λ 2	McDonald's ω	Raykov's Composite Reliability
1.	Future Time Perspective	12	0.565	0.585	0.6	0.589
		13				
		14				
2.	Academic Procrastination	1	0.669	0.672	0.7	0.684
		2				
		3				
		4				
3.	Academic Delay of Gratification	4	0.692	0.696	0.75	0.7
		5				
		8				
		9				
		10				

The Cronbach's alpha underestimation of reliability due to the violation of tau-equivalence and non-normality of data is known. Owing to this condition, alternative reliability estimates addressing this short coming, like the Guttmann lambda 2 and McDonald's Omega are reported. SPSS Statistics Ver.23.0 is used for the calculation of Cronbach's alpha and Guttman's Lambda 2. R/RStudio and Psych function are used for the estimation of McDonald's Omega and the online composite reliability calculator www.statisticalmind.com is used for the calculation of Raykov's composite reliability.

Though the reliability of the three items of future time perspective are very lowly estimated by Cronbach's alpha, Gutmman's lambda 2 and Raykov's composite, it is found to be acceptable in terms of McDonald's Omega at 0.6 (Kline, 1999). This estimate for academic procrastination and academic delay of gratification is quite acceptable at 0.7 and 0.75 respectively. Post reliability analysis, the model of volition as proposed by Dorrenbacher and Perels (2015) is validated through the statistical technique of confirmatory factor analysis, with the following results:

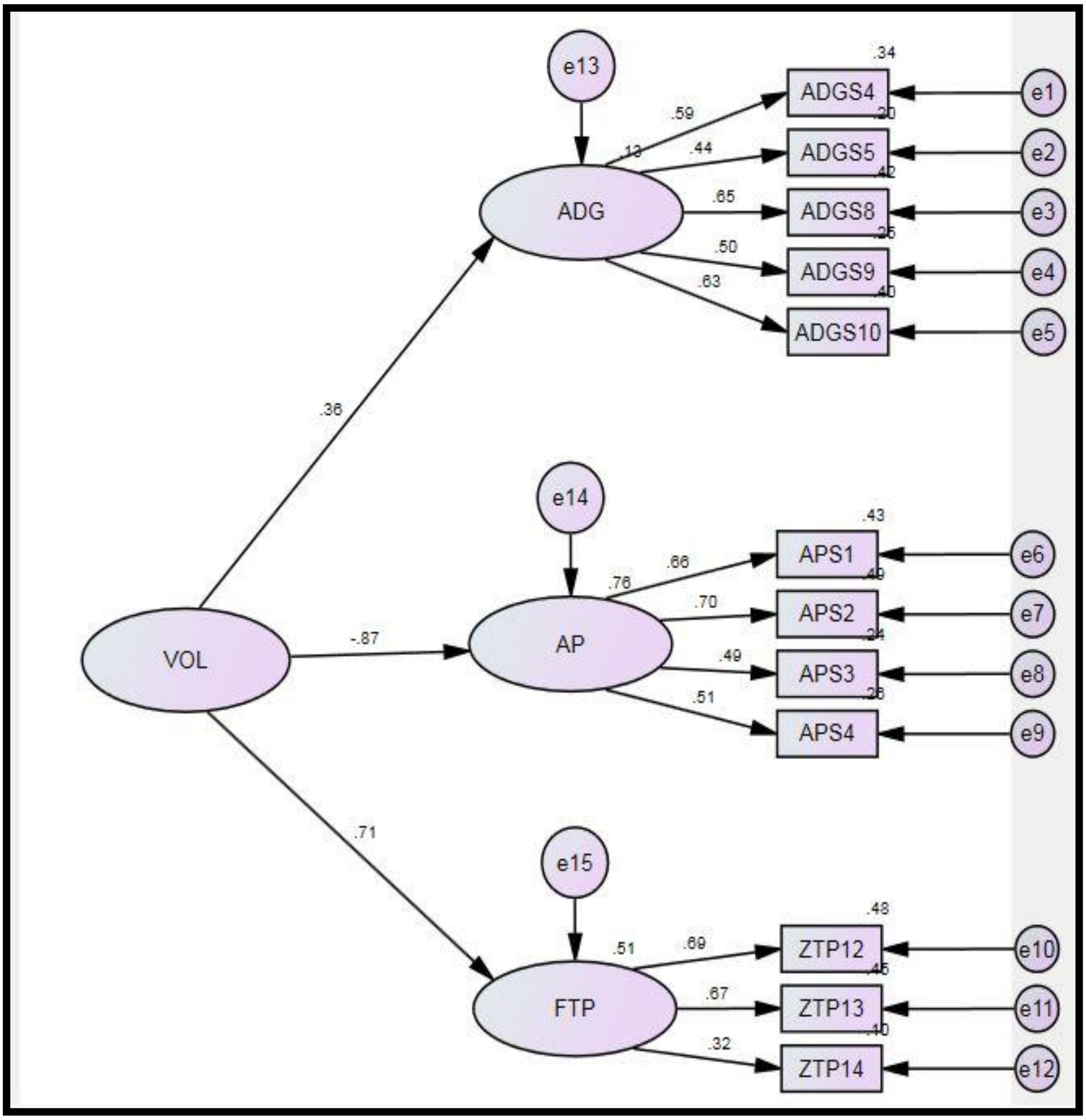


Figure 4.47 **Factor Loadings in the Path Diagram of the Factor Structure of Volition in Self Regulated Learning:**

Interpretation: Academic procrastination shares negative relationship with volition as its factor loading is -0.87. It is because the lack of this variable in a student represents the presence of volition in him or her. However, academic delay of gratification and future time perspective have positive relationship with volition as displayed by their positive factor loading of 0.36 and 0.71 respectively in concurrence with theory.

Table 4.133 Goodness of Fit Estimation - Volition in Self Regulated Learning:

Estimate	CMIN/DF	IFI	TLI	CFI	RMR	RMSEA
Benchmark	< 3.00	> 0.9	> 0.9	> 0.9	<0.08	< 0.08
Result	1.342	0.953	0.936	0.951	0.072	0.043

Interpretation: All the goodness of fit estimates display excellent estimates of their estimands, be it CMIN/DF, RMR, RMSEA or the absolute, comparative and parsimonious estimands of goodness of fit. CMIN/DF is 1.342 below the desired 3.00 value. The estimates of the estimands root mean residual and the root mean square error of approximation are 0.072 and 0.043 respectively, below the benchmark of 0.08. Incremental fit index (IFI), Tucker-Lewis Index (TLI) and Comparative Fit Index (CFI) estimates are 0.953, 0.936 and 0.951, which are well above the desired 0.9 benchmark, indicating the valid representation of volition in self regulated learning by the three variables academic delay of gratification, academic procrastination and future time perspective.

4.2.9 Application of Network Psychometrics on the Motivated Strategies for Learning Questionnaire – Revised (MSLQ- R) Sub-scales Used in the Present Research:

R Codes / Results for Conducting Exploratory Graph Analysis - MSLQ

```
> library(haven) # Import data file
> MLSQ_SRL_Variables_Data <- read_sav("D:/New Research/NP/MLSQ/MLSQ_SRL_Variables_Data.sav")
> View(MLSQ_SRL_Variables_Data)
> ega.mlsq<-EGA(MLSQ_SRL_Variables_Data, plot.EGA = TRUE)
> install.packages("EGAnet")
> library(EGAnet)
> ega.mlsq<-EGA(MLSQ_SRL_Variables_Data, plot.EGA = TRUE)
```

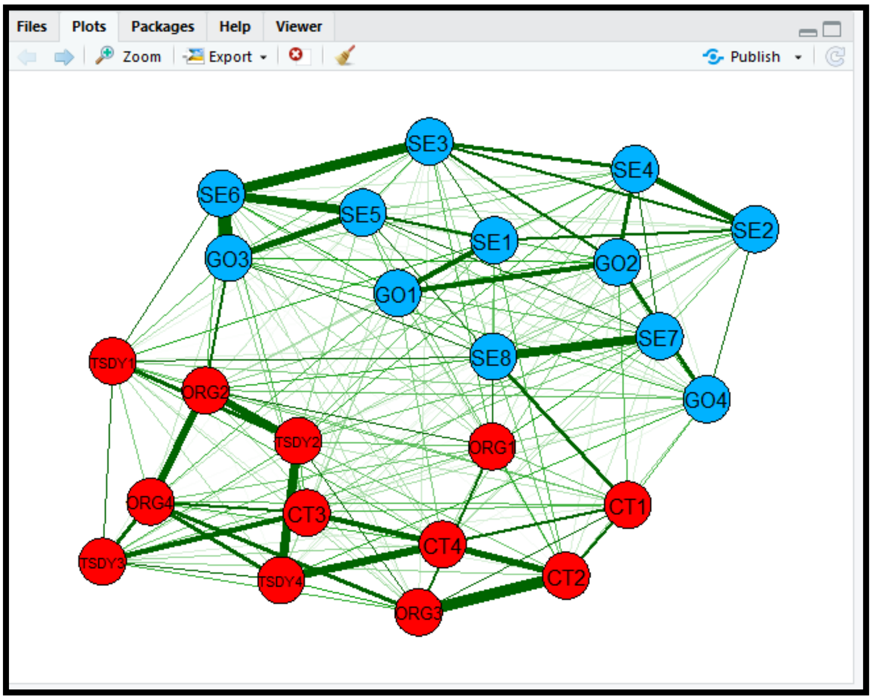


Figure 4.48 **Network Structure of the MSLQ Sub-scales**

```
> summary(ega.mlsq)
EGA Results:

Number of Dimensions:
[1] 2

Items per Dimension:
items dimension
CT1     CT1        1
CT2     CT2        1
CT3     CT3        1
CT4     CT4        1
ORG1   ORG1      1
ORG2   ORG2      1
ORG3   ORG3      1
ORG4   ORG4      1
TSDY1 TSDY1   1
TSDY2 TSDY2   1
TSDY3 TSDY3   1
TSDY4 TSDY4   1
GO1     GO1        2
GO2     GO2        2
GO3     GO3        2
GO4     GO4        2
SE1     SE1        2
```

SE2	SE2	2
SE3	SE3	2
SE4	SE4	2
SE5	SE5	2
SE6	SE6	2
SE7	SE7	2
SE8	SE8	2

Interpretation: Two dimensions are extracted, namely, motivation and learning strategies precisely. While the items of self efficacy and goal orientation form the dimension motivation, the items of critical thinking, organization and time and study environment form the dimension learning strategies.

Confirmatory Factor Analysis of the Network Model – R Codes and Results Using lavaan (Rosseel, 2012):

```
> install.packages("lavaan")
> library(lavaan)
> cfa.mlsq <- CFA(ega.obj = ega.mlsq, estimator = 'WLSMV', plot.CFA = TRUE, data = MLSQ_SRL_Variables_Data)
```

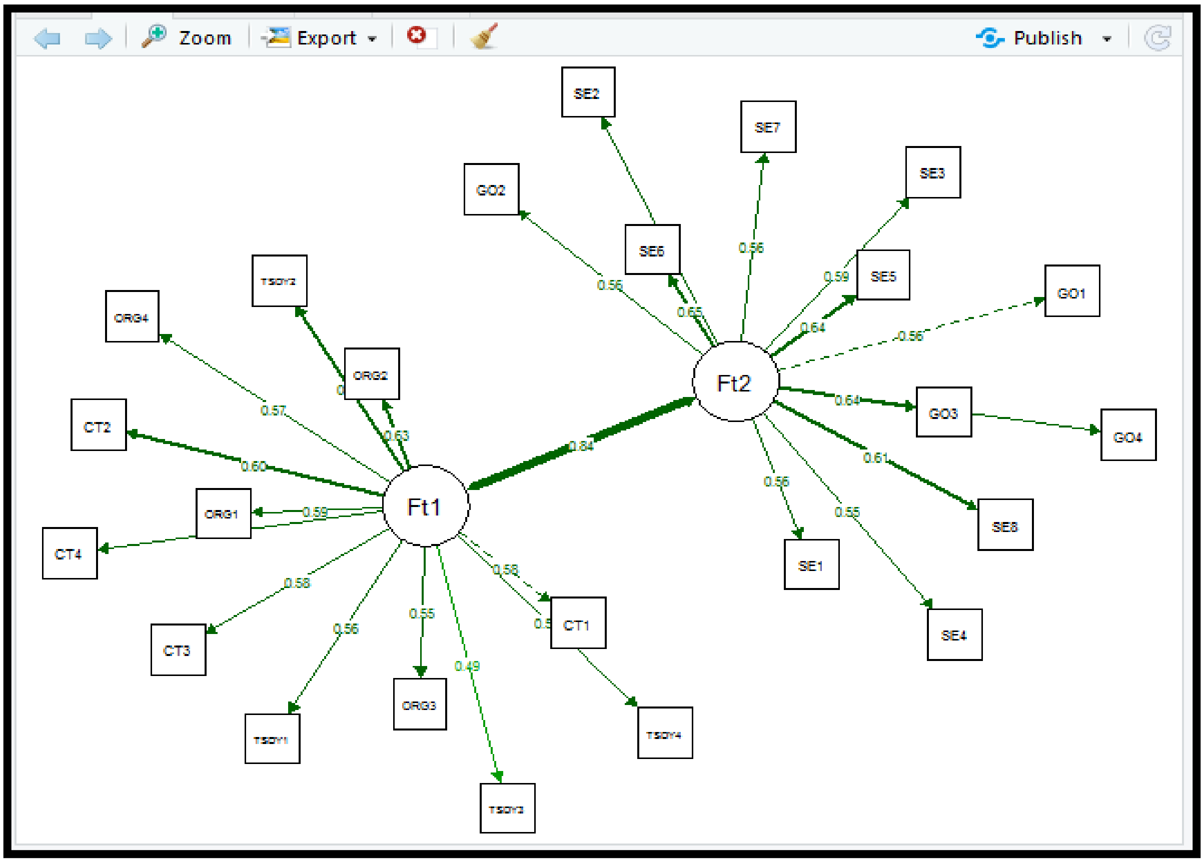


Figure 4.49 **Network Analysis Based Path Diagram with Edge-weights of the Nodes**

> lavaan::fitMeasures(cfa.mlsq$fit, fit.measures = "all")
"npar""fmin"
49.000 0.100
"chisq""df"
359.987 251.000
"pvalue"" chisq.scaled"
0.000 621.610
" df.scaled""pvalue.scaled"
251.000 0.000
"chisq.scaling.factor""baseline.chisq"
0.579 35861.596
"baseline.df """baseline.pvalue"
276.000 0.000
" baseline.chisq.scaled""baseline.df.scaled"
35861.596 276.000
"baseline.pvalue.scaled""baseline.chisq.scaling.factor"
0.000 1.000
" cfi""tli"
0.997 0.997

“nnfi”“rfi”
0.997 0.989
“nfi”“pnfi”
0.990 0.900
“ ifi”“rni”
0.997 0.997
“cfi.scaled”“tli.scaled”
0.990 0.989
“cfi.robust”“ tli.robust “
0.994 0.993
“nnfi.scaled”“nnfi.robust “
0.989 0.993
“ rfi.scaled”“nfi.scaled”
0.981 0.983
“ ifi.scaled”“rni.scaled “
0.990 0.990
“rni.robust”“rmsea “
0.994 0.016
“ rmsea.ci.lower”“rmsea.ci.upper “
0.012 0.019
“rmsea.pvalue”“rmsea.scaled “
1.000 0.029
“rmsea.ci.lower.scaled”“rmsea.ci.upper.scaled “
0.025 0.032
“rmsea.pvalue.scaled”“rmsea.robust”
1.000 0.022
“rmsea.ci.lower.robust”“rmsea.ci.upper.robust “
0.020 0.024
“ rmsea.pvalue.robust”“rmr”
NA 0.073
“ rmr_nomean”“srmr”
0.073 0.030
“srmr_bentler”“srmr_bentler_nomean”
0.030 0.030
“crmr”“crmr_nomean “
0.031 0.031
“srmr_mplus”“srmr_mplus_nomean”
0.030 0.030
“cn_05”“cn_01“
1444.224 1529.575
“gfi”“agfi”
0.994 0.993
“pgfi”“mfi”
0.832 0.970
“ecvi”
0.255

Interpretation: The robust CFI and robust TLI estimates are 0.994 and 0.993 which are well above the benchmark of 0.95. Also, the RMSEA and RMR are 0.022 and 0.03 well below as desired from the benchmark of 0.05 and 0.08 respectively. These estimates indicate excellent goodness of fit.

> View(ega.mlsq$dim.variables)

	items	dimension
CT1	CT1	1
CT2	CT2	1
CT3	CT3	1
CT4	CT4	1
ORG1	ORG1	1
ORG2	ORG2	1
ORG3	ORG3	1
ORG4	ORG4	1
TSDY1	TSDY1	1
TSDY2	TSDY2	1
TSDY3	TSDY3	1
TSDY4	TSDY4	1
GO1	GO1	2
GO2	GO2	2
GO3	GO3	2
GO4	GO4	2
SE1	SE1	2
SE2	SE2	2
SE3	SE3	2
SE4	SE4	2
SE5	SE5	2
SE6	SE6	2
SE7	SE7	2
SE8	SE8	2

> net.loads(ega.mlsq$network, ega.mlsq$wc)$std

```
1     2
CT1   0.189 0.081
CT2   0.221 0.070
CT3   0.199 0.068
CT4   0.228 0.059
ORG1  0.151 0.125
ORG2  0.178 0.125
ORG3  0.250 0.014
ORG4  0.250 0.031
GO1   0.075 0.188
GO2   0.051 0.216
GO3   0.083 0.231
GO4   0.102 0.137
TSDY1 0.143 0.115
TSDY2 0.233 0.078
TSDY3 0.202 0.025
TSDY4 0.213 0.040
```

SE1	0.083	0.174
SE2	0.030	0.196
SE3	0.040	0.238
SE4	0.045	0.211
SE5	0.039	0.266
SE6	0.085	0.243
SE7	0.073	0.182
SE8	0.127	0.172

Interpretation: As per the original factor structure, the items of critical thinking, organization and time and study environment scale load more on factor 1 of learning strategies. The items of self efficacy and goal orientation load on the factor 2 of motivation.

```
> install.packages("bootnet")
> library(bootnet)
> Network <- estimateNetwork(MLSQ_SRL_Variables_Data,default = "EBICglasso")
> install.packages("qgraph")
> library(qgraph)
> plot(Network, layout = "spring",labels = TRUE)
```

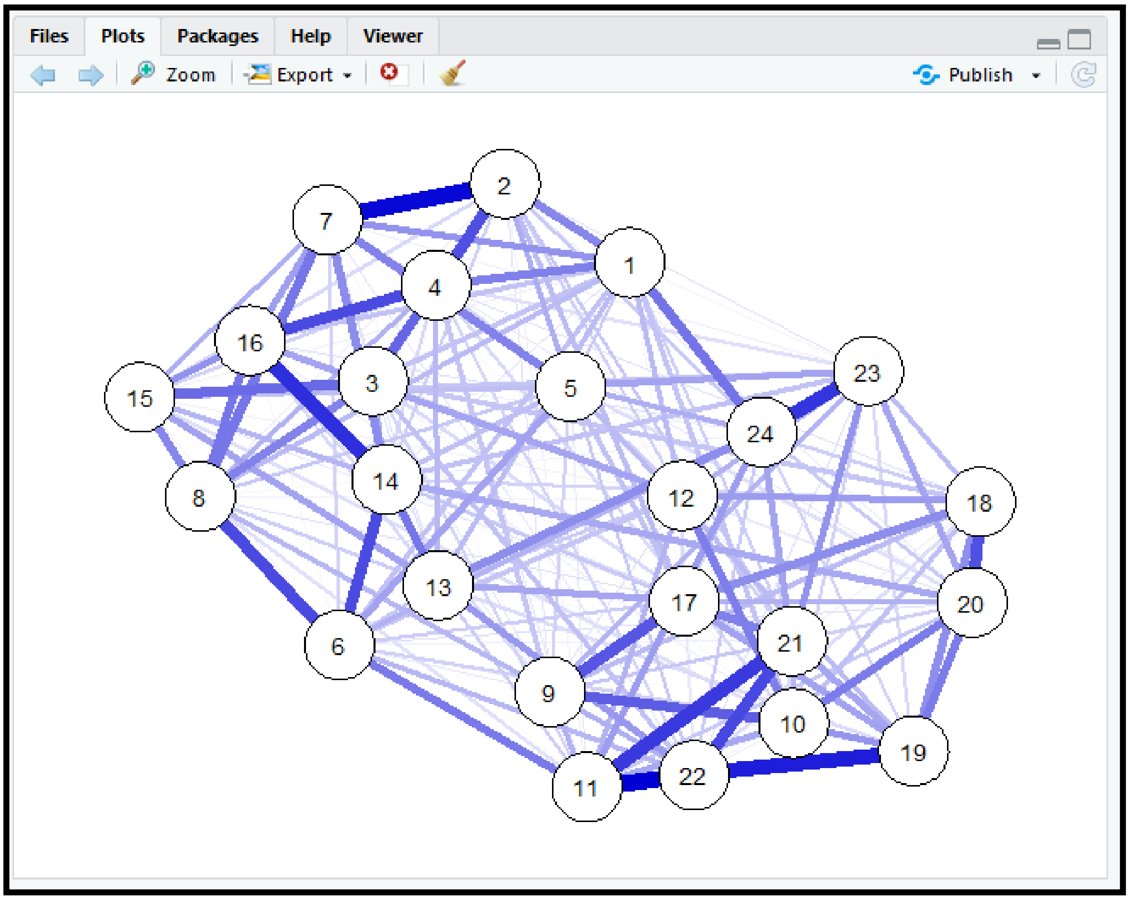


Figure 4.50 **Partial Correlation Network of MSLQ**

> centralityPlot(Network)

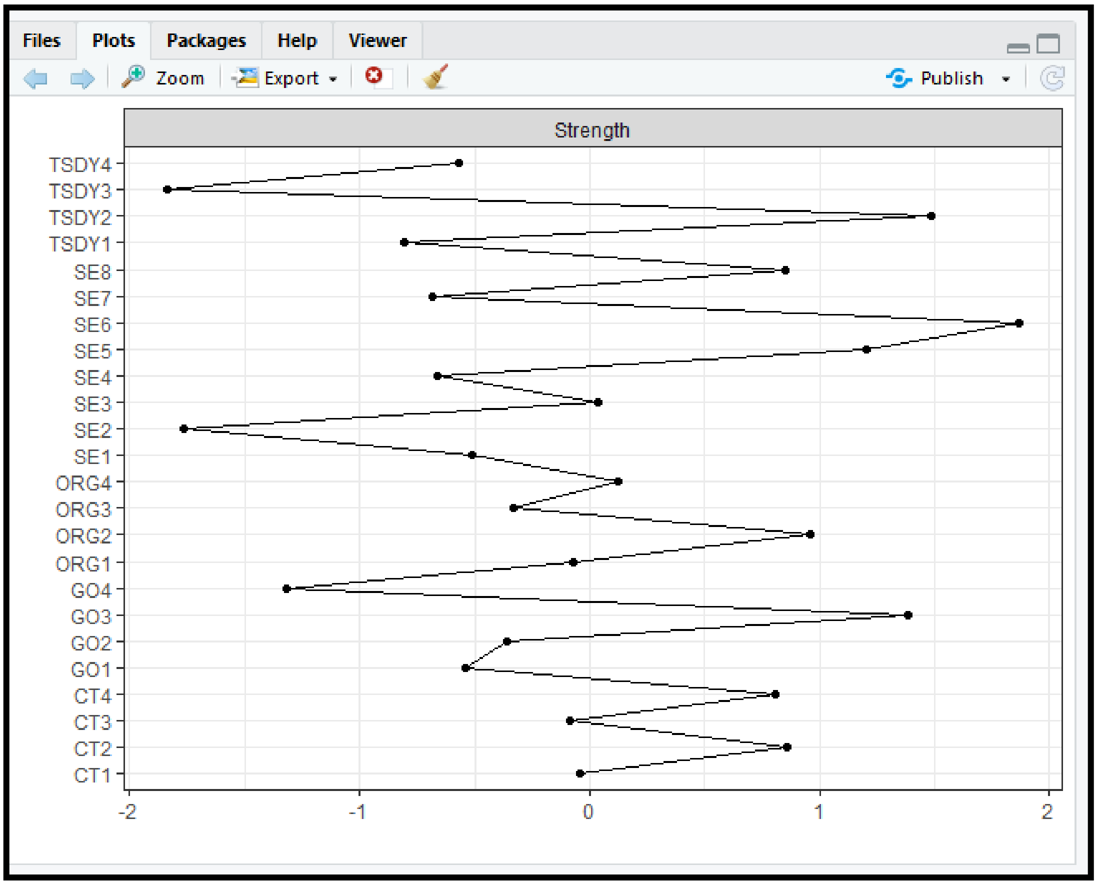


Figure 4.51 **Strength Centrality Index**

Interpretation: The strength of the node TSDY3 is the lowest and the strength of the node SE6 is highest in the network of MSLQ items.

Confidence Interval of the Edge-weights of Nodes:

```
> boot1 <- bootnet(Network, nBoots = 50,nCores = 8)
> plot(boot1, labels = FALSE, order = "sample")
```

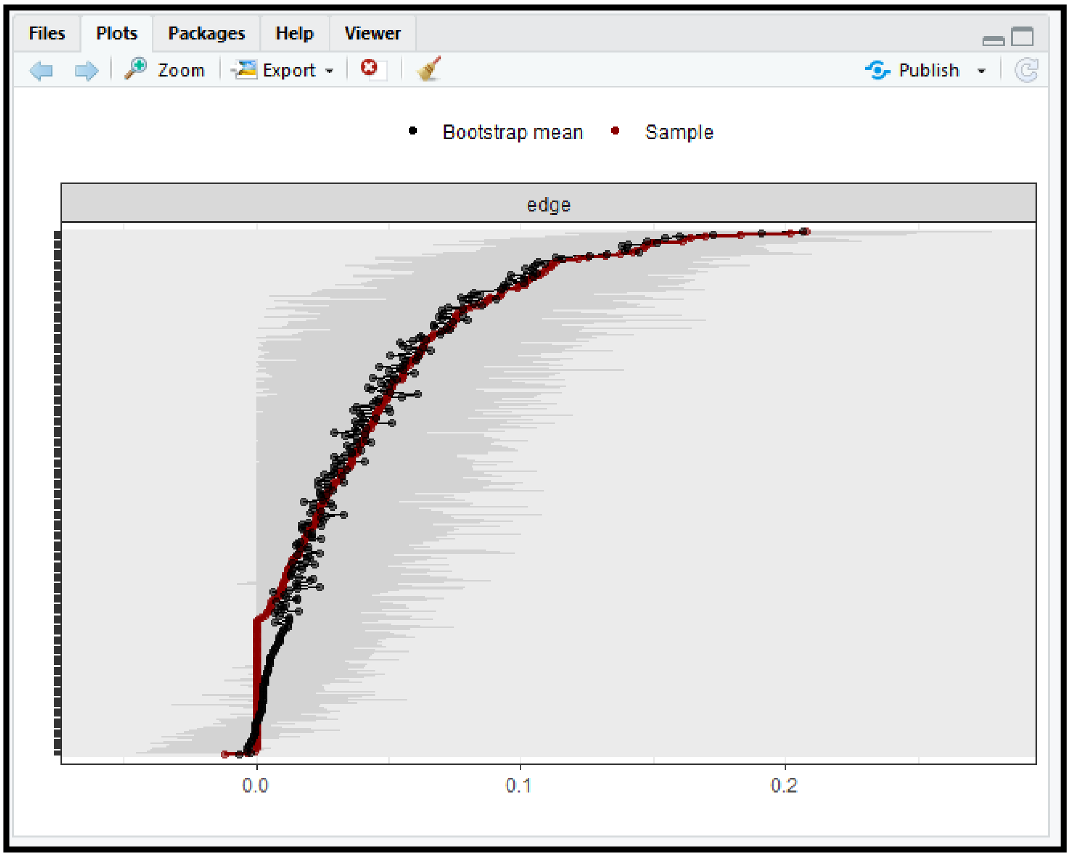


Figure 4.52 **Confidence Interval of the Edge-weights of Nodes**

```
> summary(boot1)
```

Interpretation: The confidence interval does contain zero. So the result is non-significant and the nodes do not differ significantly with each other in their edge strength.

CS-Coefficients of Strength Centrality Index Across Bootstrapped Samples:

```
> boot2 <- bootnet(Network, nBoots = 50,type = "case", nCores = 8)
>plot(boot2)
```

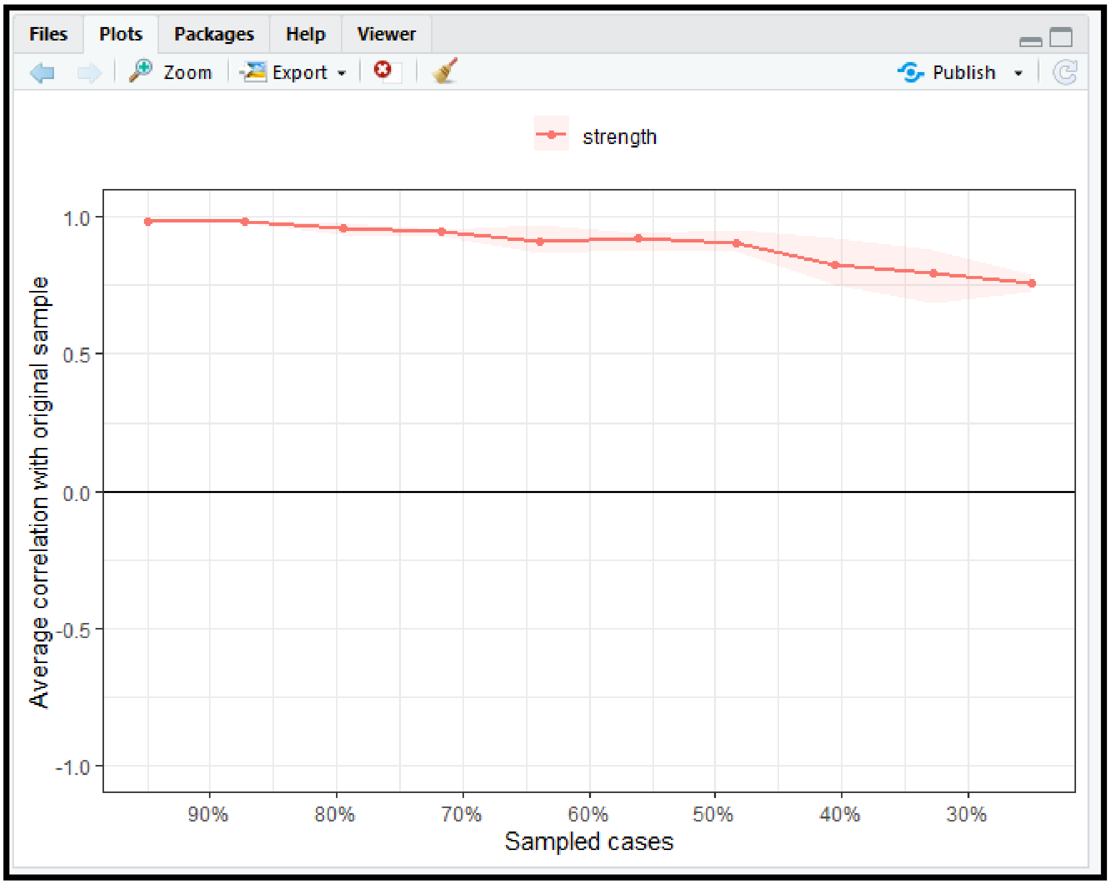


Figure 4.53 **CS-Coefficients of Strength Centrality Index Across Bootstrapped Samples**

Interpretation: Even a bootstrapped data generated using 30 percent of the original data, is able to show strong correlation of 0.7 and above of its strength central index with that of the original sample data, with 95 percent confidence. This shows high stability of the edge-weights with respect to their strengths.

Correlation Stability Analysis:

```
> corStability(boot2)
=== Correlation Stability Analysis ===
Sampling levels tested:
nPerson Drop% n
1     450  75.0 2
2     590  67.2 4
3     730  59.4 6
4     870  51.6 6
5    1009  43.9 7
6    1149  36.1 4
7    1289  28.3 8
8    1429  20.6 7
```

9   1569 12.8 3
10   1709   5.0 3
“Maximum drop proportions to retain correlation of 0.7 in at least 95% of the samples:”

edge: 0.672

strength: 0.75 (CS-coefficient is highest level tested)

Interpretation: Since the CS-coefficient is 0.75, above the benchmark of 0.7, it shows high stability of the nodes’ edge-weights with respect to their strength.

Structural Consistency:

```
> boot <- bootEGA(MLSQ_SRL_Variables_Data, n = 50, model = "glasso", type = "resampling", plot.typicalStructure = FALSE)
> sc <- dimStability(boot, orig.wc = ega.mlsq$wc)
> sc$dimensions
```

1   2
0.903 0.933

Interpretation: 11 items out of the total 12 items under learning strategies can retain their factor structure when tested in multiple bootstrapped samples, since the structural consistency coefficient is 0.903. Similarly, with the structural consistency coefficient being 0.933, 11 out of the 12 items of motivation scale can retain their factor structure when searched in multiple bootstrapped samples. The internal consistency of the time and study environment, critical thinking, organization, self efficacy and goal orientation sub scales estimated using Cronbach’s alpha are satisfactory at 0.669, 0.706, 0.687, 0.808 and 0.672 respectively. These estimates are reported in this study for the purpose of convention.

Item Stability:

```
> sc$items$plot.itemStability
```

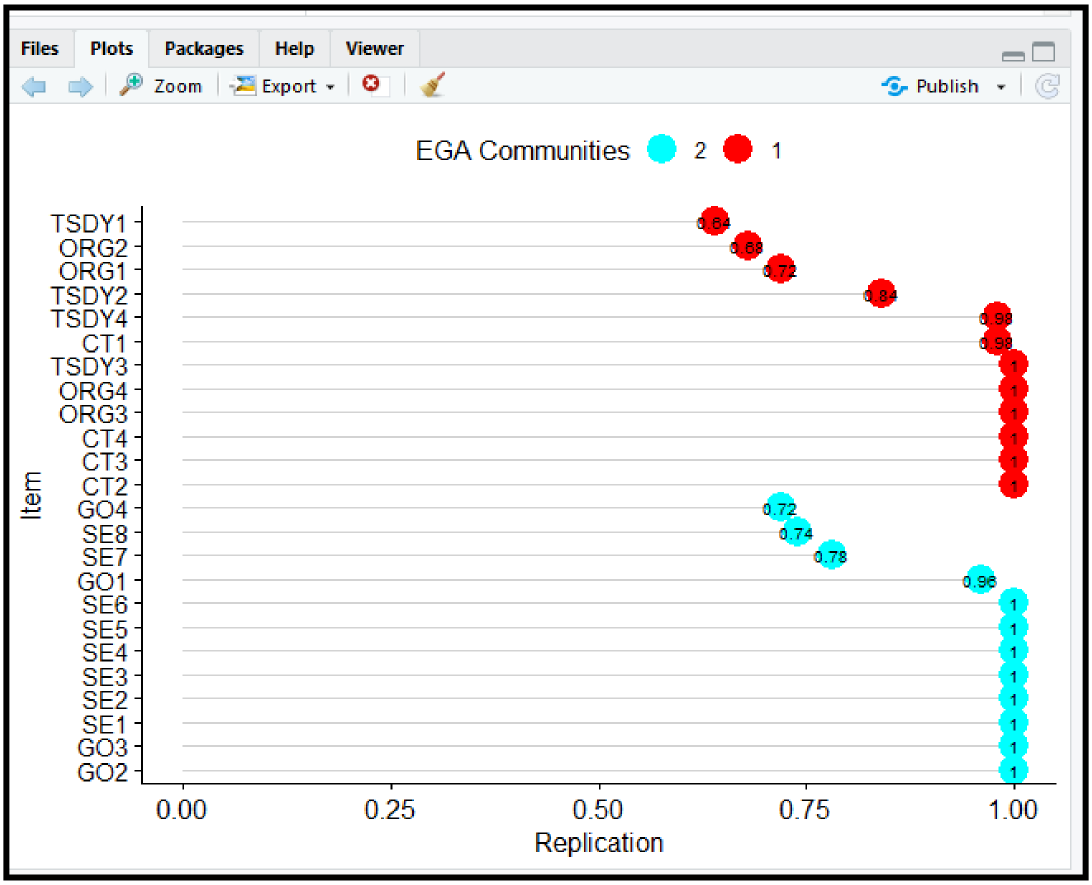


Figure 4.54 **Item Stability Across Dimensions**

> View(sc$items$item.dim.rep)

Filter

	1	2	3
TSDY1	0.64	0.1	0.26
ORG2	0.68	0.06	0.26
ORG1	0.72	0.06	0.22
TSDY2	0.84		0.16
TSDY4	0.98		0.02
CT1	0.98		0.02
TSDY3	1		
ORG4	1		
ORG3	1		
CT4	1		
CT3	1		

Showing 1 to 11 of 24 entries

Console Terminal

	1	2	3
CT2	1		
GO4	0.1	0.72	0.18
SE8	0.1	0.74	0.16
SE7	0.06	0.78	0.16
GO1		0.96	0.04
SE6		1	
SE5		1	
SE4		1	
SE3		1	
SE2		1	
SE1		1	

Showing 12 to 22 of 24 entries

GO3		1	
GO2		1	

Showing 14 to 24 of 24 entries

Interpretation: The nodes TSDY1, TSDY2, TSDY4, ORG1, ORG2, CT1, GO1, GO4, SE7 and SE8 , have the tendency to split from their parent factor and load simultaneously on other factors as well, when searched in multiple samples generated from the original data through boot strapping, reducing the structural consistency of the respective sub-scales.

4.2.10 Latent Profile Analysis of the Motivated Strategies for Learning Questionnaire – Revised (MSLQ- R) Sub-scales Used in the Present Research:

One of the assumptions made by the researchers during the validation of any psychological instrument is that, all the participants have the same level of the measured construct in them. However, in reality, the participants differ from each other with respect to the presence of the measured construct in them. They can be broadly classified as belonging to certain number of homogeneous groups called profiles, where all the members of a profile are similar to each other with respect to the estimates of a certain estimands and differ with participants of other profiles. Such an outcome is statistically possible to be achieved through the general mixture model (Harring and Hodis, 2016; Pastor et al., 2007) statistical technique called the Latent Profile Analysis (LPA), whose origin lies in developmental approaches (Magnusson and Cairns, 1996; Bergman and El-Khouri, 2003). The latent profile analysis is similar to factor analysis technique where a latent variable is assumed to exist which influences the variances in a host of manifest variables, and the technique aims to reduce the number of manifest variables into a manageable number of factors or dimensions. When the test items are replaced with the participants or persons and the latent dimensions are replaced with latent profiles, the approach becomes latent profile analysis, where it is assumed that beneath the obtained data from a sample, lies a set of homogeneous groups or profiles, into which each of the participant in the study can be associated with.

The variables used in the measurement of the parameters, like variances and covariances, using which the participants are classified, are continuous in latent profile analysis. If they are categorical, then another technique called the latent class analysis is conducted. Here, data of each of the continuous variables forms a distribution of its own, where every observation is assigned a probability for belonging to a sample or profile from a population of same dataset. From this heterogenous general mixture model, a homogenous group of participants is tried to be extracted by estimating the fit of data with certain pre-determined models, because of which latent profile analysis is called a model-based clustering technique (Hennig et al., 2015; Scrucca et al., 2017).

There are six models of LPA which differ from each other based on the manner in which they measure or do not measure the parameters variance and co-variance, along with mean which is measured always. These six models are:

Table 4.134 Models of Latent Profile Analysis:

S.No.	Variance	Covariance	Model
1.	Equal	0	1 (Simplest)
2.	Varying	0	2
3.	Equal	Equal	3
4.	Equal	Varying	4 (in Mplus)
5.	Varying	Equal	5 (in Mplus)
6.	Varying	Varying	6 (Most Complex)

Models 4 and 5 can be estimated using MPlus software only. The rest of the four models can be estimated using the free-software package tidyLPA (2019) of

R/RStudio (2016). The models 1 to 6 are arranged based on the increasing order of their complexity. The model 1 is the simplest and the most popular one. Here, only the mean of the participants from each profile is estimated. The variances of the each profile group are assumed to be same and the covariance is fixed at zero. The most complex model 6 takes into account the reality and hence makes no assumption. But, when the model is simple, it might not fit the data well and lack internal validity, but its external validity through the replication of results when applied using a fresh data set is high. When the model is complex, its internal validity is high as the data fits the model very well, but the changes of the replication of the estimates using afresh data comes down bringing down along with it the external validity of the data (Rosenberg et al., 2019). The steps involved in latent profile analysis can be listed as model specification, estimation of profiles, plotting the profiles, comparing of the solutions, getting the estimates of parameters and fitness of models.

Several types of fit indices estimates are used to find the model specification and its associated latent class, to finally estimate the number of profiles (Araujo et al., 2019). Some of the most commonly reported estimates are:

Table 4.135 Most Commonly Reported Fit Indices in Latent Profile Analysis:

S.No.	Estimand	Meaning
1.	AIC: Aikake information criterion	Goodness of fit estimate which penalizes the model when its number of parameters increase. Lower the value, better the model fitness.
2.	BIC: Bayesian information criterion	Goodness of fit estimate which penalizes the model when its number of parameters increase, better than AIC. Lower the value, better the model fitness.
3.	SABIC: Sample size-adjusted Bayesian information criterion	Goodness of fit estimate which penalizes the model when its number of parameters increases, taking into consideration the sample size. Lower the value, better the model fitness.
4.	Entropy:	A measure of uncertainty in the classification of profiles, reverse-coded hence 1 means complete certainty in profile classification, and 0 means complete uncertainty

5.	Prob. Min.:	Lowest value of the diagonal of the average latent class probabilities for most likely class membership, as per the assigned profiles. It should be as high as possible, meaning that the cases are assigned to profiles which they must belong with a high probability
6.	Prob. Max.:	Greatest value of the diagonal of the average latent class probabilities for most likely class membership, as per the assigned profiles. It should be as high as possible, meaning that the cases are assigned to profiles which they must belong with a high probability
7.	N Min.:	Depending on the most probable profile membership, the number of sample subjects assigned to the smallest profile
8.	N Max.:	Depending on the most probable profile membership, the number of sample subjects assigned to the largest profile
10.	BLRT p-value:	p-value for the bootstrapped likelihood ratio test. Significant p-value less than 0.05 represents goodness of fit between the model and the data.

The present study applied the latent profile analysis technique on the five sub-scales of MSLQ-R Indian version validated by (Chechi, Bhalla and Chakraborty, 2019), namely, organization, critical thinking, time and study environment from learning strategies scale and self efficacy and goal orientation from the motivation scale.

Table 4.136 Details of the Used MSLQ-R Sub-scales:

S.No.	Scale	Variable	Items
1.	Motivation	Intrinsic Goal Orientation	1,16,22,24 (4)
2.		Self-Efficacy for Learning and Performance	5,6,12,15,20,21,29,31(8)
3.	Learning Strategy	Organization	32,42,49,63 (4)
4.		Critical Thinking	47,51,66,71 (4)
5.		Time Management and Study Environment	35,43, 65,70 (4)

The sample of the study comprised of 1799 undergraduate and post graduates from the Majha, Malwa and Doaba regions of the Indian state of Punjab, belonging to the disciplines of Commerce, Science, Business Administration and Computer Application. Permission was taken from the head of the institutions to conduct the questionnaire administration on the subjects during regular class sessions. The students were selected using simple random selection technique and they took 15-20 minutes to fill and return the questionnaire back to the investigator. The extraction of profiles as part of latent profile analysis is conducted using the *tidyLPA* package of R Ver. 3.6.3. along with the package *dplyr*. Model 1 where the variance is equal and covariance is zero and model 6 where both of them are varying were selected to estimate the profiles. Estimate_profiles and compare_solutions functions help in finding the optimum number of profiles. Help of estimands AIC. BIC, entropy and BLRT- p value were taken to finally settle for the number of profiles. The graphical representation of the profiles was presented by plot-profile function. The estimates of the profiles are obtained using get_estimates and get_data.

R Codes and Results of Latent Profile Analysis:

Below are given the R Codes and results of Latent Profile Analysis:

1. Import data file in r
2. > install.packages("tidyLPA")
3. > library(tidyLPA)
4. Install package dplyr
5. > library (dplyr)

```
> MLSQ_SRL_Variables_Data%>%select(CT,ORG,GO,TSDY,SE)%>%single_imputation() %>%
estimate_profiles(1)
tidyLPA analysis using mclust:

Model Classes AIC      BIC      Entropy prob_min prob_max n_min n_max BLRT_p
1     1       27322.10 27377.05 1.00    1.00     1.00     1.00  1.00

> MLSQ_SRL_Variables_Data%>%select(CT,ORG,GO,TSDY,SE)%>%single_imputation() %>%
estimate_profiles(2)
tidyLPA analysis using mclust:

Model Classes AIC      BIC      Entropy prob_min prob_max n_min n_max BLRT_p
```

1 2 24460.22 24548.14 0.81 0.94 0.95 0.47 0.53 0.01

> MLSQ_SRL_Variables_Data%>%select(CT,ORG,GO,TSDY,SE)%>%single_imputation() %>% estimate_profiles(3)
tidyLPA analysis using mclust:

Model Classes AIC BIC Entropy prob_min prob_max n_min n_max BLRT_p
1 3 23410.45 23531.34 0.82 0.88 0.93 0.14 0.52 0.01
> MLSQ_SRL_Variables_Data%>%select(CT,ORG,GO,TSDY,SE)%>%single_imputation() %>% estimate_profiles(4)
tidyLPA analysis using mclust:

Model Classes AIC BIC Entropy prob_min prob_max n_min n_max BLRT_p
1 4 23028.69 23182.55 0.79 0.86 0.90 0.07 0.40 0.01
> MLSQ_SRL_Variables_Data%>%select(CT,ORG,GO,TSDY,SE)%>%single_imputation() %>% estimate_profiles(5)
tidyLPA analysis using mclust:

Model Classes AIC BIC Entropy prob_min prob_max n_min n_max BLRT_p
1 5 22885.21 23072.04 0.80 0.68 0.91 0.04 0.39 0.01
> MLSQ_SRL_Variables_Data%>%select(CT,ORG,GO,TSDY,SE)%>%single_imputation() %>% estimate_profiles(6)
tidyLPA analysis using mclust:

Model Classes AIC BIC Entropy prob_min prob_max n_min n_max BLRT_p
1 6 22752.74 22972.54 0.76 0.71 0.91 0.05 0.32 0.01

Table 4. 137 Summary of Model 1 Specifications for Class Selection:

Model	Classes	AIC	BIC	Entropy	Prob_min	Prob_max	n_min	n_max	BLRT_p
1	1	27322.1	27377.05	1.00	1.00	1.00	1.00	1.00	-
	2	24460.22	24548.14	0.81	0.94	0.95	0.47	0.53	**0.01**
	3	**23410.45**	**23532.34**	**0.82**	**0.88**	**0.93**	**0.14**	**0.52**	
	4	23028.69	23182.55	0.79	0.86	0.9	0.07	0.4	
	5	22885.21	23072.04	0.8	0.68	0.9	0.04	0.32	
	6	22752.74	22972.54	0.76	0.71	0.91	0.05	0.32	

Interpretation: Though AIC and BIC estimates-wise, profile 3 is not the lowest, its entropy is highest at 0.82, which means that 82 percent of the cases of total 1799, that is 1475 cases, were properly classified into their most probable profile. 88 percent of the cases belonging to the lowest profile could be properly classified under this category as the Prob_min is 0.88. Since Prob_max is 0.93. It means that 93 percent cases belonging from the higher group were properly classified into its respective category. The number of cases in the lowest profile is 252 as the n-min is 0.14. The number of cases in the highest profile is 935. The rest of the cases comprising 34 percent, that is, 611 cases form theaverage group. The goodness of fit between the model and the data is very significant with p-value less than 0.05 at 0.01of the estimand BLRT_p-value

```
> MLSQ_SRL_Variables_Data %>% select(CT,ORG,GO,TSDY,SE)%>%single_imputation() %>%
estimate_profiles(3, variances = "varying", covariances = "varying")
tidyLPA analysis using mclust:
Model Classes AIC      BIC      Entropy prob_min prob_max n_min n_max BLRT_p
6     3       21999.31 22340.00 0.58    0.69     0.89     0.09  0.63  0.01
```

Table 4. 138 Summary of Model 1 and Model 6 Specifications for Class Selection:

Model	Classes	AIC	BIC	Entropy	Prob_min	Prob_max	n_min	n_max	BLRT_p
1	3	23410.45	23532.34	0.82	0.88	0.93	0.14	0.52	0.01
6		21999.31	22340	0.58	0.69	0.89	0.09	0.63	0.01

Interpretation: When the number of parameters is high, the model estimation is the best. This is apparent since the AIC and BIC values of the model 6 estimating 3 profiles are less than the AIC and BIC values of the model 1 estimating 3 profiles. The entropy of the model 6 is very low though when compared to model 1. Both the model results are significant at 0.01 p-value of boot strap likelihood ratio test (BLRT). A comparison of the estimates of classes 1,2 and 3 under model 1 and model 3 is shown below:

```
>MLSQ_SRL_Variables_Data %>%
select(CT,ORG,GO,TSDY,SE)%>%single_imputation() %>% estimate_profiles(1:3,
variances = c("equal", "varying"), covariances = c("zero",
"varying"))%>%compare_solutions(statistics = c("AIC", "BIC"))
Compare tidyLPA solutions:
```

Model	Classes	AIC	BIC
1	1	27322.104	27377.053
1	2	24460.225	24548.145
1	3	23410.446	23531.335
6	1	22753.962	22863.862
6	2	22075.499	22300.794
6	3	21999.310	22339.999

Best model according to AIC is Model 6 with 3 classes.

Best model according to BIC is Model 6 with 2 classes.

An analytic hierarchy process, based on the fit indices AIC, AWE, BIC, CLC, and KIC (Akogul & Erisoglu, 2017), suggests the best solution is Model 6 with 3 classes.

```
>MLSQ_SRL_Variables_Data %>% select(CT,ORG,GO,TSDY,SE)%>%single_imputation() %>% estimate_profiles(1:3, variances = c("equal", "varying"), covariances = c("zero", "varying"))%>%compare_solutions(statistics = c("Entropy", "BIC"))
```

Compare tidyLPA solutions:

Model	Classes	Entropy	BIC
1	1	1.000	27377.053
1	2	0.806	24548.145
1	3	0.823	23531.335
6	1	1.000	22863.862
6	2	0.468	22300.794
6	3	0.582	22339.999

Best model according to Entropy is Model NA with NA classes.

Best model according to BIC is Model 6 with 2 classes.

An analytic hierarchy process, based on the fit indices AIC, AWE, BIC, CLC, and KIC (Akogul & Erisoglu, 2017), suggests the best solution is Model 6 with 3 classes.

Interpretation: All the estimates of the least strict (model 1) and the most strict (model 6) model specifications, show that the number of estimated classes or profiles for the present data is 3. They are termed as high SRL group, average SRL group and the low SRL group. The most popular model 1 estimates has been used for reporting the final results.

```
> 
MLSQ_SRL_Variables_Data%>%select(CT,ORG,GO,TSDY,SE)%>%single_imputation() %>% estimate_profiles(3)%>%plot_profiles()
```

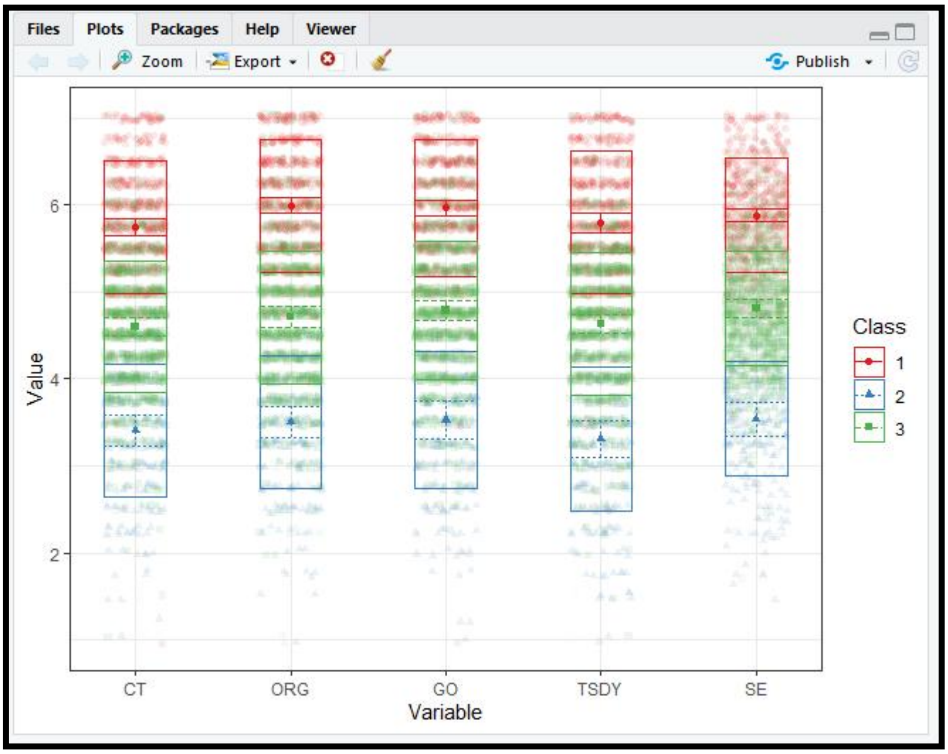


Figure 4.55 **Latent Profiles of MSLQ-R**

Interpretation: The low SRL group 2 in the above plot of profiles, is consistently low across all the variables of motivation and learning strategies sub-scales. The high SRL group 1, is consistently high across all the variables. Similarly, the average group represented by the profile 3, is so across all the variables of SRL.

```
>m <- MLSQ_SRL_Variables_Data%>%select(CT,ORG,GO,TSDY,SE)%>%single_imputation() %>% estimate_profiles(3)

>get_estimates(m)
```

A tibble: 30 x 8

	Category	Parameter	Estimate	se	p	Class	Model	Classes
	<chr>	<chr>	<dbl>	<dbl>	<dbl>	<int>	<dbl>	<dbl>
1	Means	CT	5.75	0.0501	0.	1	1	3
2	Means	ORG	5.99	0.0441	0.	1	1	3
3	Means	GO	5.97	0.0402	0.	1	1	3
4	Means	TSDY	5.79	0.0507	0.	1	1	3
5	Means	SE	5.88	0.0348	0.	1	1	3

```
 6 Variances CT       0.576 0.0278 3.61e- 95     1     1       3
 7 Variances ORG      0.590 0.0281 7.05e- 98     1     1       3
 8 Variances GO       0.626 0.0299 1.82e- 97     1     1       3
 9 Variances TSDY     0.675 0.0355 1.47e- 80     1     1       3
10 Variances SE       0.429 0.0180 3.70e-125     1     1       3
# ... with 20 more rows
```

```
>m <- MLSQ_SRL_Variables_Data%>%select(CT,ORG,GO,TSDY,SE)%>%single_imputation() %
estimate_profiles(1:3)
>get_estimates(m)
# A tibble: 60 x 8
   Category  Parameter Estimate        se     p Class Model Classes
   <chr>     <chr>        <dbl>     <dbl> <dbl> <int> <dbl>   <int>
 1 Means     CT            4.82  0.000658     0     1     1       1
 2 Means     ORG           4.97  0.000718     0     1     1       1
 3 Means     GO            5.01  0.000712     0     1     1       1
 4 Means     TSDY          4.84  0.000749     0     1     1       1
 5 Means     SE            4.99  0.000566     0     1     1       1
 6 Variances CT            1.18  NaN        NaN     1     1       1
 7 Variances ORG           1.29  NaN        NaN     1     1       1
 8 Variances GO            1.28  NaN        NaN     1     1       1
 9 Variances TSDY          1.35  NaN        NaN     1     1       1
10 Variances SE            1.02  NaN        NaN     1     1       1
# ... with 50 more rows
```

Interpretation: The estimates of the estimands for a particular profile under a specific model, or for a range of profiles can be obtained as shown above using the get_estimate function and a declared dataframe in r.

```
>get_fit(m)
# A tibble: 3 x 18
Model Classes  LogLik    AIC    AWE    BIC   CAIC    CLC    KIC  SABIC    ICL
<dbl>   <dbl>   <dbl>  <dbl>  <dbl>  <dbl>  <dbl>  <dbl>  <dbl>  <dbl>  <dbl>
    1       1 -13651. 27322. 27480. 27377. 27387. 27304. 27335. 27345. -27377.
    2       1 -12214. 24460. 24714. 24548. 24564. 24430. 24479. 24497. -24785.
    3       1 -11683. 23410. 23761. 23531. 23553. 23368. 23435. 23461. -23887.
# ... with 7 more variables: Entropy <dbl>, prob_min <dbl>, prob_max <dbl>,
#   n_min <dbl>, n_max <dbl>, BLRT_val <dbl>, BLRT_p <dbl>
```

Interpretation: Similarly, the estimates of the goodness of fit for a particular profile under a specific model, or for a range of profiles can be obtained as shown above using the get_fit function and a declared dataframe in r.

4.3 Classical Test Theory Based Scale Purification of the Items Instruments:

According to Wieland et al. (2017) and Wieland et al. (2018), scale purification is mostly is done taken into quantitative aspects of the items. But, along with the statistical criteria, qualitative judgemental aspects of retaining or eliminating of items should also be taken into account while conducting scale purification.

Under the quantitative aspects of scale purification, some of the vital estimands to be taken into account are the measure of central tendency mean under descriptive statistics, communality and total variance explained obtained during exploratory factor analysis, factor loading, Tucker-Lewis Index (TLI) and Comparative Fit Index (CFI) obtained during confirmatory factor analysis and Item-total correlation along with internal consistency Cronbach’s alpha obtained during reliability analysis.

An item which is capable in measuring its associated factor, would possess estimates above and beyond the benchmarks of these multiple estimands. However, due to sampling error, an item’s performance can vary across these different measures of interest during scale purification.

Since the estimate of Cronbach’s alpha underestimates the true reliability of a scale under the violation of tau-equivalence and normality conditions, alternate measures of reliability, like greatest lower bound reliability and Raykov’s composite reliability are also taken into account, to compare and contrast the mentioned underestimation of reliability by Cronbach’s alpha and also obtain accurate measure of reliability of the studied variables.

Table 4.139 Classical Test Theory Based Scale Purification of the Original Instruments Items:											
Component I					Cognition					GLB/CR	Final Status of the Item
Dimension I					Critical Thinking						
Item.No.	TVE	TLI	CFI	RMSEA	Mean	Communality	Item-total Correlation	Reliability-Internal Consistency	FL		
M47.	53.201%	0.963	0.975	0.049	4.759	0.502	0.469	0.706(0.657)	0.58	0.716/0.706	Retained
M51.					4.842	0.557	0.511	0.706(0.631)	0.64		Retained
M66.					4.792	0.51	0.475	0.706(0.654)	0.59		Retained
M71.					4.877	0.559	0.512	0.706(0.631)	0.64		Retained
Dimension II					Organization						
Item.No.	TVE	TLI	CFI	RMSEA	Mean	Communality	Item-total Correlation	Reliability-Internal Consistency	FL	GLB/CR	
M32.	51.623%	0.963	0.975	0.049	4.973	0.496	0.456	0.687(0.63)	0.57	0.717/0.69	Retained
M42.					5.036	0.533	0.481	0.687(0.615)	0.62		Retained
M49.					4.861	0.503	0.461	0.687(0.629)	0.49		Retained
M63.					5.019	0.533	0.482	0.687(0.614)	0.63		Retained
Component II					Metacognition						
Dimension III					Planning						
Item.No.	TVE	TLI	CFI	RMSEA	Mean	Communality	Item-total Correlation	Reliability-Internal Consistency	FL	GLB/CR	
P2.	73.256%	0.948	0.961	0.069	3.6	0.715	0.653	0.817(0.766)	0.74	0.818/0.818	Retained
P3.					3.38	0.763	0.699	0.817(0.718)	0.83		Retained
P5.					3.361	0.719	0.657	0.817(0.762)	0.75		Retained
Dimension IV					Self Recording						
Item.No.	TVE	TLI	CFI	RMSEA	Mean	Communality	Item-total Correlation	Reliability-Internal Consistency	FL	GLB/CR	
SR10.	61.041%	0.948	0.961	0.069	3.276	0.534	0.532	0.787(0.764)	0.66	0.814/0.789	Retained
SR11.					3.228	0.631	0.611	0.787(0.726)	0.67		Retained
SR12.					3.323	0.692	0.664	0.787(0.697)	0.74		Retained
SR14.					3.361	0.584	0.571	0.787(0.746)	0.71		Retained
Dimension V					Self Evaluation						
Item.No.	TVE	TLI	CFI	RMSEA	Mean	Communality	Item-total Correlation	Reliability-Internal Consistency	FL	GLB/CR	
Seval15.	66.090%	0.948	0.961	0.069	3.485	0.601	0.609	0.826(0.803)	0.73	0.86/0.831	Retained
Seval16.					3.247	0.679	0.675	0.826(0.77)	0.75		Retained
Seval18.					3.228	0.732	0.711	0.826(0.755)	0.78		Retained
Seval20.					3.361	0.631	0.621	0.826(0.795)	0.71		Retained
Component III					Motivation						
Sub Component - I					Volition						
Dimension VI					Academic Delay of Gratification						
Item.No.	TVE	TLI	CFI	RMSEA	Mean	Communality	Item-total Correlation	Reliability-Internal Consistency	FL	GLB/CR	Final Status of the Item
ADG4.	45.258%	0.875	0.958	0.077	2.951872	0.490491	0.476828	0.692 (0.629)	0.58	0.754/0.696	Retained
ADG5.					2.604278	0.325713	0.357932	0.692 (0.681)	0.44		Retained
ADG8.					3.053476	0.550075	0.520709	0.692 (0.612)	0.67		Retained
ADG9.					2.524064	0.380165	0.399945	0.692 (0.662)	0.47		Retained
ADG10.					2.807487	0.516480	0.488371	0.692 (0.625)	0.63		Retained
Dimension VII					Academic Procrastination						
AP1.	50.475%	0.941	0.955	0.041	2.818	0.554	0.478	0.667(0.580)	0.64	0.71/0.678	Retained
AP2.					3.016	0.634	0.546	0.667(0.534)	0.7		Retained
AP3.					2.732	0.4	0.377	0.667(0.646)	0.47		Retained
AP4.					3.090	0.431	0.399	0.667(0.634)	0.53		Retained
Dimension VIII					Future Time Perspective						
ZTP12.	53.845%	0.941	0.955	0.041	3.213	0.638	0.432	0.565(0.371)	0.71	0.59/0.585	Retained
ZTP13.					3.465	0.66	0.461	0.565(0.33)	0.65		Retained
ZTP14.					3.47	0.317	0.25	0.565(0.632)	0.31		Retained
Sub – Component II					Motivational Beliefs						

Dimension IX					Self Efficacy						
Item.No.	TVE	TLI	CFI	RMSEA	Mean	Communality	Item-total Correlation	Reliability-Internal Consistency	FL	GLB/CR	Final Status of the Item
M5.	42.858%	0.96	0.972	0.051	5.034	0.391	0.493	0.808(0.791)	0.55	0.836/0.805	Deleted
M6					4.668	0.359	0.47	0.808(0.795)	0.52		Deleted
M12.					5.248	0.468	0.552	0.808(0.782)	0.63		Retained
M15.					4.775	0.405	0.507	0.808(0.789)	0.56		Retained
M20.					5.076	0.492	0.569	0.808(0.78)	0.65		Retained
M21.					5.301	0.487	0.564	0.808(0.781)	0.65		Retained
M29.					4.801	0.390	0.492	0.808(0.791)	0.55		Deleted
M31.					5.043	0.436	0.528	0.808(0.786)	0.59		Retained
Dimension X					Academic Intrinsic Motivation						
Item.No.	TVE	TLI	CFI	RMSEA	Mean	Communality	Item-total Correlation	Reliability-Internal Consistency	FL	GLB/CR	Final Status of the Item
AIM10	43.546	0.91	0.936	0.08	4.602	0.505	0.584	(0.814)0.785	0.65	0.856/0.815	Retained
AIM17					4.684	0.413	0.514	(0.814)0.795	0.58		Retained
AIM24					4.553	0.395	0.5	(0.814)0.797	0.55		Retained
AIM9					4.648	0.313	0.432	(0.814)0.806	0.48		Retained
AIM16					4.737	0.389	0.493	(0.814)0.798	0.56		Retained
AIM8					4.684	0.466	0.55	(0.814)0.79	0.63		Retained
AIM15					4.652	0.584	0.644	(0.814)0.775	0.73		Retained
AIM22					4.542	0.419	0.518	(0.814)0.795	0.58		Retained
Dimension XI					Goal Orientation						
Item.No.	TVE	TLI	CFI	RMSEA	Mean	Communality	Item-total Correlation	Reliability-Internal Consistency	FL	GLB/CR	Final Status of the Item
M1.	50.478%	0.995	0.998	0.022	5.047	0.497	0.445	0.67(0.61)	0.58	0.688/0.676	Retained
M16.					4.922	0.54	0.48	0.67(0.585)	0.62		Retained
M22.					5.259	0.53	0.472	0.67(0.592)	0.61		Retained
M24.					4.803	0.453	0.414	0.67(0.628)	0.53		Retained
Component IV					Behavior						
Dimension XII					Time and Study Environment						
Item.No.	TVE	TLI	CFI	RMSEA	Mean	Communality	Item-total Correlation	Reliability-Internal Consistency	FL	GLB/CR	Final Status of the Item
M35.	50.328%	0.984	0.995	0.039	5.119	0.472	0.427	0.669(0.617)	0.54	0.695/0.674	Retained
M43.					4.878	0.571	0.5	0.669(0.57)	0.67		Retained
M65.					4.684	0.451	0.416	0.669(0.626)	0.52		Retained
M70.					4.663	0.519	0.46	0.669(0.595)	0.6		Retained
Component V					Emotions						
Dimension XIII					Reappraisal						
Item.No.	TVE	TLI	CFI	RMSEA	Mean	Communality	Item-total Correlation	Reliability-Internal Consistency	FL	GLB/CR	Final Status of the Item
Reapp1.	49.541%	0.977	0.988	0.048	3.403226	0.384808	0.425	0.741 (0.728)	0.5	0.772/0.749	Retained
Reapp2					3.185484	0.523169	0.531	0.741 (0.686)	0.62		Retained
Reapp3.					3.524194	0.596721	0.585	0.741 (0.666)	0.71		Retained
Reapp4.					3.768145	0.483509	0.492	0.741 (0.701)	0.6		Retained
Reapp5.					3.060484	0.488847	0.497	0.741(0.698)	0.6		Retained
Dimension XIV					Suppression						
Item.No.	TVE	TLI	CFI	RMSEA	Mean	Communality	Item-total Correlation	Reliability-Internal Consistency	FL	GLB/CR	Final Status of the Item
Supp1.	43.499%	0.918	0.959	0.072	3.364919	0.423156	0.42	0.675 (0.628)	0.52	0.716/0.673	Retained
Supp2.					3.522177	0.407764	0.41	0.675 (0.632)	0.51		Retained
Supp3.					3.691532	0.425755	0.421	0.675 (0.628)	0.53		Retained
Supp4.					3.441532	0.469929	0.453	0.675 (0.612)	0.58		Retained
Supp5.					3.463710	0.448361	0.439	0.675 (0.619)	0.56		Retained

Table 4.140 List of Retained Items Per Variable Post CTT Based on Scale Purification of Original Instruments:

S.No.	SRL Variable	Original Tool Items	Retained Items	Retaining Percentage %
1.	Critical Thinking	5	4	80
2.	Organization	4	4	100
3.	Planning	7	3	43
4.	Self Recording	7	4	57
5.	Self Evaluation	6	4	66.66
6.	Self Efficacy	8	5	62.5
7.	Goal Orientation	4	4	100
8.	Academic Intrinsic Motivation	12	8	66.6
9.	Future Time Perspective	4	3	75
10.	Academic Procrastination	5	4	80
11.	Academic Delay of Gratification	10	5	50
12.	Time and Study Environment	8	4	50
13.	Reappraisal	5	5	100
14.	Suppression	5	5	100
		90	**62 + 5 Fillers = 67**	**69%**

4.4 Item Response Theory Based Scale Purification of the Items Instruments:

The performance of the items of a scale are studied under Item response theory (IRT) approach based on the probability of selecting a specific response of the items by the subjects of the study P(θ) over the measured personality trait θ. Owing to this reason, the IRT based scale purification is considered to be sample free and item specific in nature. There are two categories of item response theory (IRT), namely, parametric (PIRT) and non-parametric (NIRT) item response theories (Sijtsma and Molenaar, 2002; Olivares, 2005). Since the parametric classical test theory (CTT) based scale purification approach is subject or sample based and suggests that the estimates of the estimands would change on conducting the same exercise on another sample, the non-parametric item response theory (IRT) based scale purification is hence taken upon.

Infact, when the assumptions of item response theory, namely, unidimensionality, local independence and monotonicity, are satisfied, along with model-fitting under parametric IRT, the approach leads to invariance of item and ability parameters (Avsar and Tevesancil, 2017; Hambelton and Swaminathan, 1985). This is how IRT achieves superiority over CTT.

The parametric item response theory for Likert-scale based ordinal response scales can be carried out under polytomous IRT with graded response model (GRM) as the preferred choice for researchers (Ostini and Nering, 2006; DeMars, 2010). Here, a non-linear relationship is assumed between the probability of selecting a specific response of the items by the subjects P(θ) and the measured personality trait θ (Embretson and Resie, 2000). However, large data set is required for achieving model-fit which is always a challenge with PIRT, paving the way for the introduction of non-parametric item response theory NIRT (Stout,2001), which require lesser assumptions than its other counterpart (Stochl, 2007). NIRT's application is wide-spread on ordinal scales (Sijtsma, 2005).

While the estimators of PIRT are 2PL, 3PL, Normal ogive and Graded response model, the estimators of NIRT are broadly divided into Mokken model and non-parametric regression estimation model. The former is further divided into Monotone Homogeneiry model (MHM) and the double monotonicity model (DMM). The latter is divided into Kernal Smooting approach model (KSAM) and Isotonic and smoothened isotonic regression models (Sijtsma and Molennar, 2002; Lee, 2007).

Scale purification using parametric item response theory is conducted using the functions *mirt, ltm and psych* in R/RStudio software. The Graded response model (GRM) of parameter estimation is used for the generation of item discrimination index parameter of polytomous ordinal response items. Two basic models known as the unconstrained and the constrained models are tested as part of IRT based scale purification to estimate the discrimination index. In the constrained model, all the items are assumed to be equally good in discriminating the subjects. The model is called constrained because the discrimination parameter is not allowed to change as part of this analysis. In the unconstrained model, items are assumed to vary in their ability to discriminate subjects based on their responses. The better model is chosen from goodness of fit estimation through a significant p-value.

The items are then estimated graphically through the generation of Item Characteristic Curve (ICC), Item Information Curve (IIC) and Test Information Function Curve (TIC). The Item Response Category Characteristic Curve displays the probability of subjects selecting a certain option on the Likert scale at different levels of the latent trait. An item is better at discriminating between subjects when the curves are peaked and spread across all levels of the latent trait.The Item Information Curve displays the extent to which an item accurately measure the latent variable at its different levels of the presence in subjects. Some items perform well in measuring the presence of the attribute at low levels, while other items provide more information at higher levels of the variables' presence in subjects. The analog of ICC in response or options of the scale is the Option Characteristic Curve (OCC) which graphically displays the performance of every option of an item over different levels of the measured latent attribute (Mazza et al., 2014). The Test Information Function Curve is the summation of the Item Information Curves of all the items. It tells us how well the entire test performs in the measurement of the latent trait at various levels of its presence in the subjects and is desired to peak at about the mean of the sample as it is at the mean that the highest number of individuals would be expected to lie (Rizopoulos, 2006).

The Steps / sample Rcodes for conducting the IRT based scale purification on Polytomous Ordinal Response Items are:

1. Load the data file.
2. Install the functions psych and ltm
3. Library (psych) # Activate the function
4. Library (ltm) # Activate the function
5. Fit1<-grm(data file, constrained = TRUE) # Constarined model estimation
6. Fit1 # Here the obtained discrimination parameter is same for all items
7. Fit2<-grm(data file, constrained = FALSE) # Unconstarined model estimation
8. Fit2 # The discrimination parameter index of every item is obtained now

9. Anova (Fit1,Fit2) # Runs the better model testing, where a significant p-value indicate that unconstrained model 2 is better than constrained model 1.
10. plot(fit2.agree, lwd = 2, cex = 0.8,legend = TRUE, cx = "topright",xlab = "Agreeableness", cex.main = 1,cex.lab = 1, cex.axis = 1) # For generation of Item Characteristic curve of every item
11. plot(fit2.agree, type = "IIC", lwd = 2,cex = 0.8, legend = TRUE,cx = "topleft", xlab = "Agreeableness",cex.main = 1, cex.lab = 1, cex.axis = 1) # For generation of Item Information curve of every item
12. plot(fit2.agree, type = "IIC", items = 0, lwd = 2, xlab = "Agreeableness",cex.main = 1, cex.lab = 1, cex.axis = 1) # For generation of Test Information curve of the test
13. plot(x, plottype = c("OCC", "EIS", "density", "expected", "sd", "triangle", "tetrahedron", "RCC", "EISDIF", "OCCDIF", "PCA", "expectedDIF", "densityDIF"), items = "all", subjects, axistype = c("scores", "distribution"), alpha, main, xlab, ylab, xlim, ylim, cex) # For generation of Option Characteristic curve of every item, which also be generated using the TestGraph software (Ramsay, 2000).

There are two possible ways of generation of option characteristic curves, namely the parametric IRT (PIRT) and the non parametric IRT (NIRT). The former assumes the presence of a parametric structure under which a parameter vector is estimated which provides the items statistics involving its discrimination and difficulty (Mazza, Punzo and McGuire, 2014), as discussed above. On the contrary, the latter, generates the ICCs and OCCs without assuming any mathematical form for them, which are considered to represent the true ICCs / OCCs (Van der Linden and Hambleton (1997).

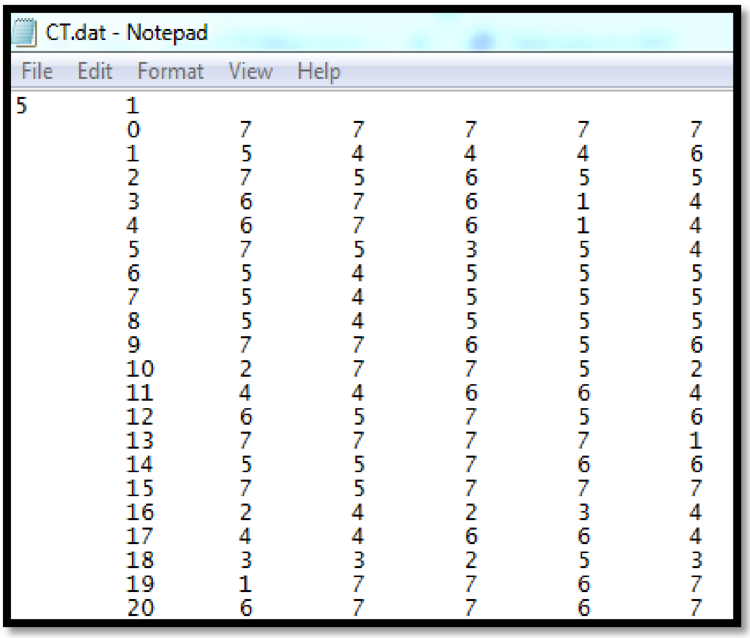
One of the important non-parametric item response model under the non-parametric regression estimation model is the Kernal smoothing approach method (KSAM). The technique generates ICC and OCC curves for each item of a scale. The ICC of an item must be monotone and steeper to qualify the item as a good discriminating one. The OCC curves must be such that the item must measure the trait for all the levels of the scale. The subjects with low level of the latent trait must select option 1, the moderate level subjects should select option 4 and the individuals with high latent trait must select the option 7 in a seven point Likert scale measuring a hidden psychological trait. A free software that applies the kernel smoothing technique to generate NIRT based ICCs and OCCs is the TestGraf software. It is used in the present study for the Generation of NIRT based OCCs and ICCs of the items of the original instruments for the sake of scale purification.

According to Ramsay (2000), "TestGraf is designed to aid the development, evaluation, and use of multiple choice examinations, psychological scales, questionnaires, and similar types of data." The software and its manual can be freely downloaded the link ego.psych.mcgill.ca/pub/ramsay/testgraf.

The scale chosen for showing the working of the software is the critical thinking sub-scale of the MSLQ scale by Pintrich et,al. (1991). It has five items and seven responses, varying from 1 = Does not correspond at all to 7 = Corresponds exactly. There are three steps involved in the generation of NIRT based OCCs and ICCs through the TestGraf98 software using kernel smotting technique. They are:

Stage 1: Reading the Data:

1. Setting the raw data for analysis.



5	1					
	0	7	7	7	7	7
	1	5	4	4	4	6
	2	7	5	6	5	5
	3	6	7	6	1	4
	4	6	7	6	1	4
	5	7	5	3	5	4
	6	5	4	5	5	5
	7	5	4	5	5	5
	8	5	4	5	5	5
	9	7	7	6	5	6
	10	2	7	7	5	2
	11	4	4	6	6	4
	12	6	5	7	5	6
	13	7	7	7	7	1
	14	5	5	7	6	6
	15	7	5	7	7	7
	16	2	4	2	3	4
	17	4	4	6	6	4
	18	3	3	2	5	3
	19	1	7	7	6	7
	20	6	7	7	6	7

Figure 4.56 **Reading of the Data in TestGraf98**

As shown in the figure above, the raw data is to be placed in a notepad file with .dat extension (CT.dat), with the first row consisting of the number of items in the scale (shown as 5 in the figure, as there are five items in the sample scale) and followed by 1, which is the number of label character.

The second row consists of the column value 0 besides which there are columns with the highest option in the scale (the sample scale is a seven point Likert scale as thus would comprise of 7 columns with the value 7. From the third row onwards, the responses of the responds are to be placed.

2. Launch the software TestGraf98.

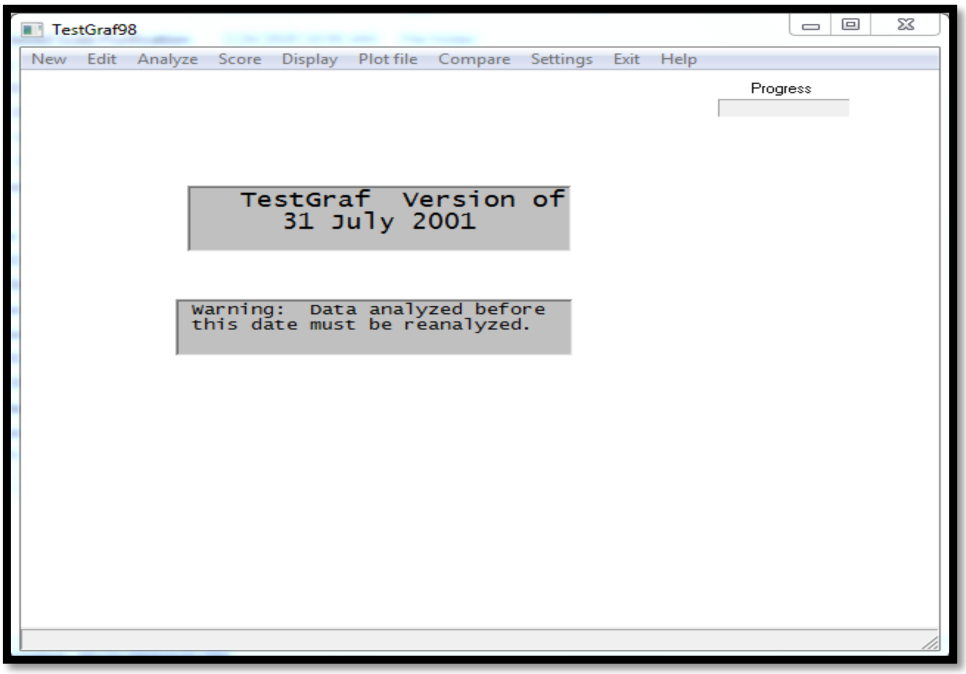


Figure 4.57 **Launch the Software – TestGraf98**

3. Click New in the menu section. The new file data dialog bog appears to selecting the .dat data file. Select the .dat file post navigation into the stored folder and click OK.

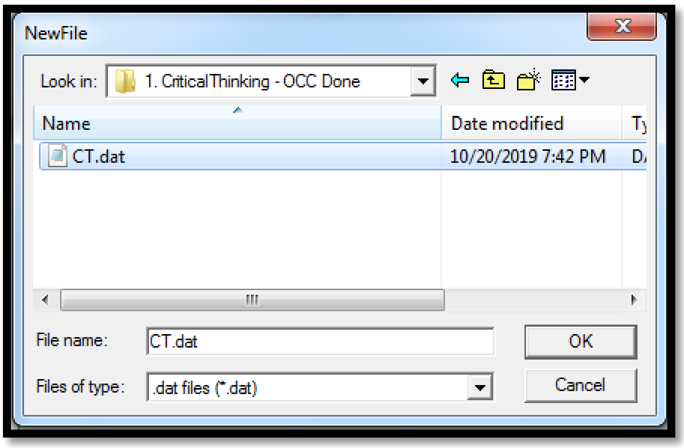


Figure 4.58 **Navigation to Datafile – TestGraf98**

4. The Information of New Test dialog box appears.

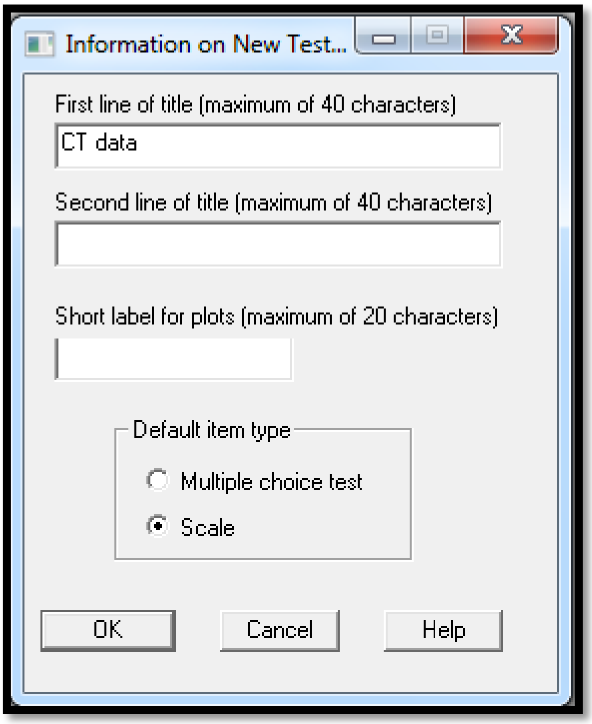


Figure 4.59 **Settings – TestGraf98**

Select the radio button Scale under Default Item Type. Click OK.

5. Click Analyze in the File menu. The Information on Format of Data to be Analyzed dialog box appears.

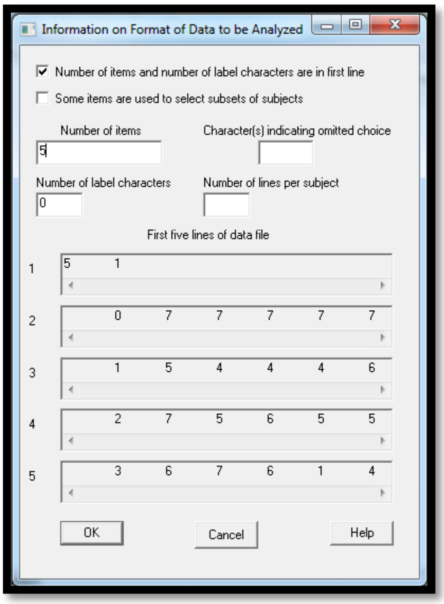


Figure 4.60 **Information on Format of Data to be Analyzed – TestGraf98**

Check the first box and enter the number of items (shown as 5 in the figure). Click OK. The Finished dialog box appears indicating the successful completion of stage 1. Click OK.

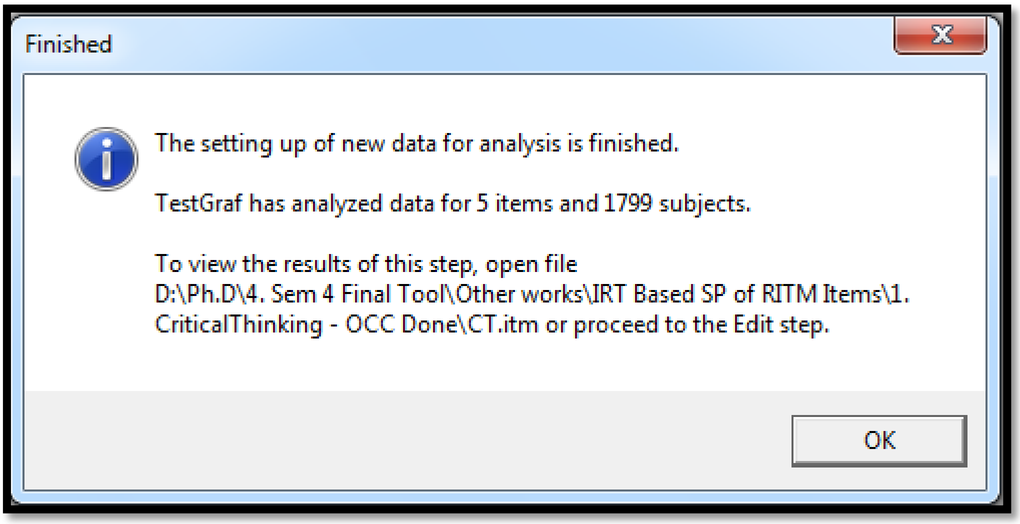


Figure 4.61 **Finished Dialog Box– TestGraf98**

Stage 2: Analyzing the Data:

1. Click Analyze in the file menu. The Analyzefile file dialog box appears, with the file of interest possessing .tg extension. Select it and click Open.

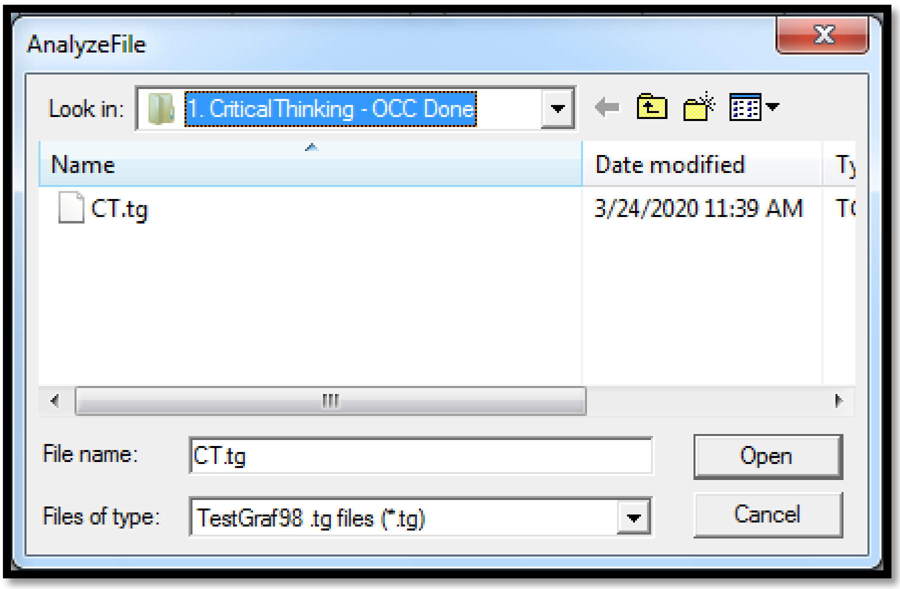


Figure 4.62**AnalyzeFile Dialog Box – TestGraf98**

The Analysis Options dialog box appears. Enter the smoothing parameter as 0.56 instead of the 0.24 shown by default. The more the value is of the smoothing parameter, the more is the information regarding the item lost. However, higher values of the smoothing parameter, allows the running of the analysis smoothly.

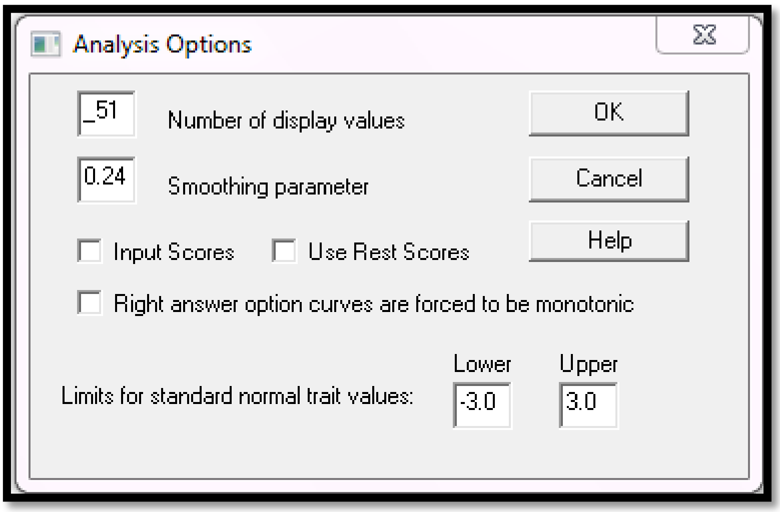


Figure 4.63**AnalyzOptions Dialog Box – TestGraf98**

This completes the analysis stage as confirmed by the appearance of Analysis finished dialog box. Click OK.

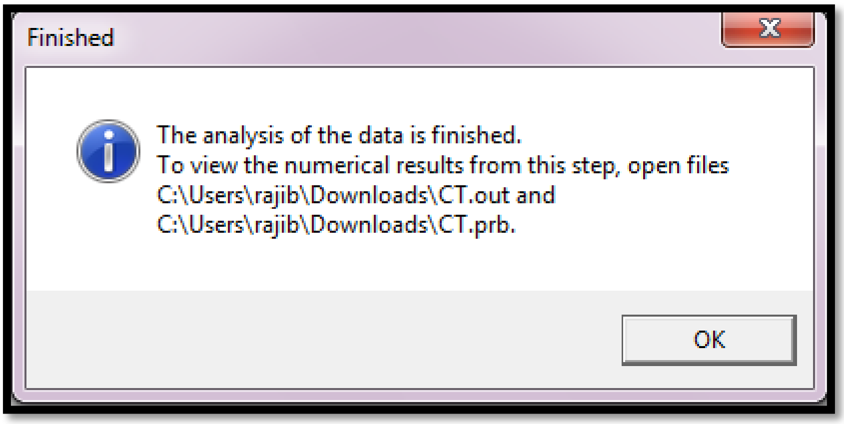


Figure 4.64**Finished Dialog Box – TestGraf98**

Stage 3: Display of OCCs and ICCs

1. Select Display in the file menu. The DispFile dialog box appears. Choose the auxillary file automatically displayed by the software with .tg extension. Click open.

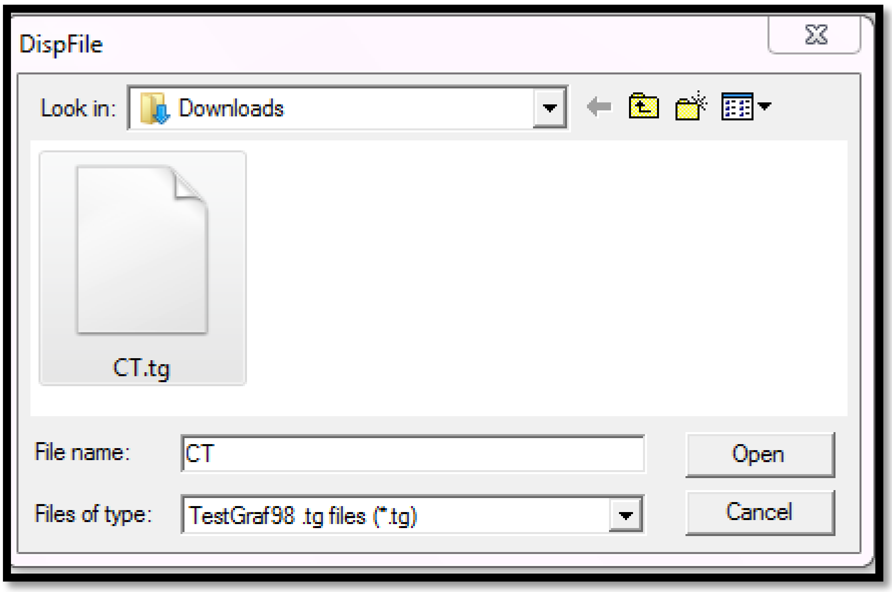


Figure 4.65**DispFile Dialog Box – TestGraf98**

2. The Next Display? dialog box appears. Select Options followed by Items click OK to obtain the OCCs and ICCs of the analyzed items.

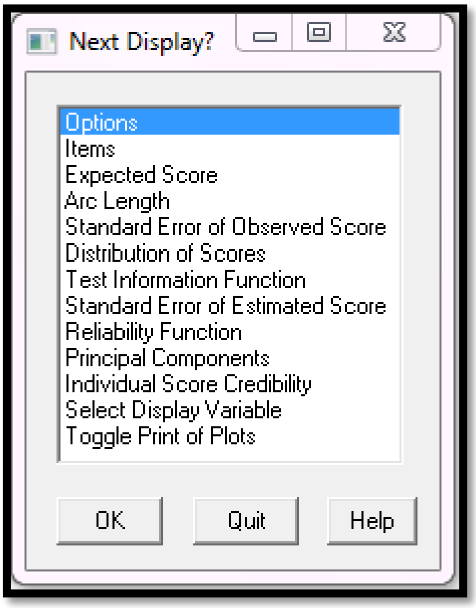


Figure 4.66**Next Display ? Dialog Box – TestGraf98**

The following OCCs and ICCs curves sample item of the scale is displayed:

Item 1 OCC and ICC:

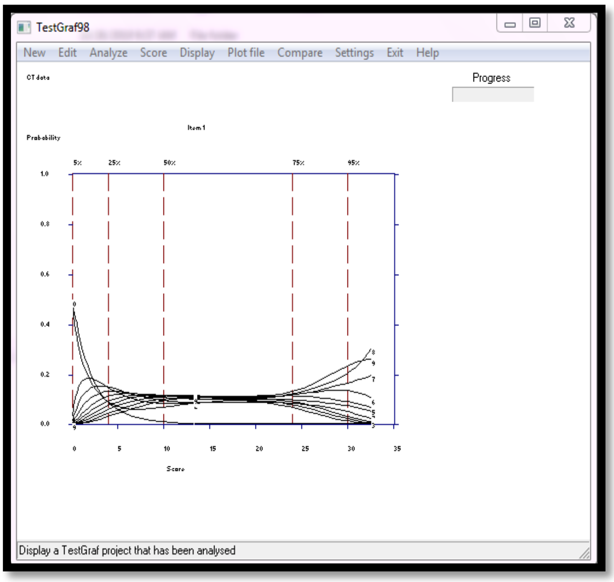


***Figure 4.67* Option Characteristic Curve (OCC) – TestGraf98**

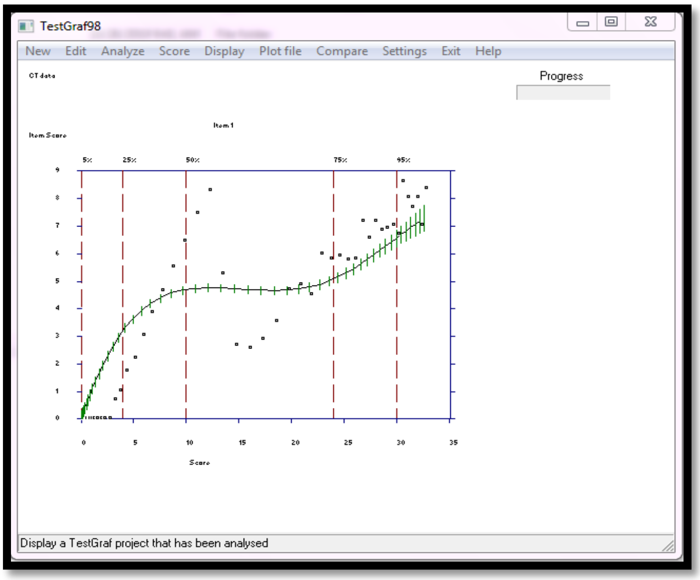


*Figure 4.68*Item Characteristic Curve (ICC) – TestGraf98

Interpretation: The curves of different options in the OCC curves for a worthy item should be dispersed and clearly distinguishable from each other all along the x-axis for different ranges of the options. Item 1 options of the sample scale are far from displaying such behavior and the ICC curve is also less than clearly ascending in nature. Its flatness at the centre clearly displays its inability to distinguish subjects having varied levels of the latent trait in the average category.

The obtained details of the items during scale purification using the estimand item discrimination and the other generated curves for all the 62 item, as part of parametric item response theory are as follows:

Table 4.141 Item Discrimination Index of the Original and Retained SRL Items:

S.No.	SRL Variable	Original Tool Items	Item Discrimination Indices of Original Items	Retained Items	Item Discrimination Indices of Retained Items	Retaining Percentage %
1.	Critical Thinking	5	M38-1.296	4	M47-1.529	80
			M47-1.597		M51-1.728	
			M51-1.652		M66-1.513	
			M66-1.547		M71-1.720	
			M71-1.691			
2.	Organization	4	M32-1.479	4	N/A	100
			M42-1.707		N/A	
			M49-1.466		N/A	
			M63-1.650		N/A	
3.	Planning	7	Plan1-0.897	3	Plan2 – 2.12	43
			Plan2-2.16		Plan3 – 3.072	
			Plan3-3.743		Plan5 – 2.12	
			Plan4- 1.411			
			Plan5 – 2.000			
			Plan6 – 1.464			
			Plan7- 1.58			
4.	Self Recording	7	Srec8-1.33	4	Srec10-1.473	57
			Srec9-0.958		Srec11-1.9	
			Srec10-1.518		Srec12-2.407	
			Srec11-2.128		Srec14-1.74	
			Srec12-1.74			
			Srec13-1.171			
			Srec14-1.891			
5.	Self Evaluation	6	Seval15-1.492	4	Seval15-1.602	66.66
			Seval16-1.911		Seval16- 1.956	
			Seval17-1.78		Seval18-3.059	
			Seval18-3.313		Seval20-1.978	
			Seval19-1.33			
			Seval20-1.953			
6.	Self Efficacy	8	M5-1.362	5	M12-1.685*	62.5
			M6-1.214		M15-1.295	
			M12-1.66		M20-1.856*	
			M15-1.402		M21-2.066*	

			M20-1.843		M31-1.445*	
			M21-1.854			
			M29-1.372*			
			M31-1.548			
7.	Goal Orientation	4	M1-1.403	4	N/A	100
			M16-1.624		N/A	
			M22-1.662		N/A	
			M24-1.282		N/A	
8.	Academic Intrinsic Motivation	12	IMa2-0.891	8	Ima9-1.034	66.6
			Ima9-1.144		Ima16-1.322	
			Ima16-1.412		Imk10-1.538	
			Ima23-1.159		Imk17-1.504	
			Imk3-1.303		Imk24-1.295	
			Imk10-1.495		Imse8-1.611	
			Imk17-1.672		Imse15-2.314	
			Imk24-1.181		Imse22-1.337	
			Imse1-0.927			
			Imse8-1.484			
			Imse15-2.202			
			Imse22-1.138			
9.	Future Time Perspective	4	ZTP11- -0.233	3	ZTP12- 1.896	75
			ZTP12- 1.964		ZTP13- 1.683	
			ZTP13- 1.625		ZTP14- 0.68	
			ZTP14- 0.684			
10.	Academic Procrastination	5	APS1-1.715	4	APS1-1.712	80
			APS2-2.040		APS2-2.343	
			APS3-1.043		APS3-0.994	
			APS4-1.288		APS4-1.167	
			APS5-0.817			
11.	Academic Delay of Gratification	10	ADGS1-1.295	5	ADGS4- 1.501*	50
			ADGS2- -0.523		ADGS5- 0.953	
			ADGS3- 1.43		ADGS8- 2.072*	
			ADGS4- 1.91		ADGS9- 1.067	
			ADGS5- 0.888		ADGS10- 1.792*	
			ADGS6 – 1.113			
			ADGS7- -0.777			
			ADGS8- 1.361			

			ADGS9- 1.077			
			ADGS10- 1.501			
12.	Time and Study Environment	8	M35-1.32	4	M35- 1.339	50
			M43-1.596		M43- 1.849	
			M52- -0.508		M65- 1.25	
			M65-1.309		M70- 1.459	
			M70-1.545			
			M73-1.282			
			M77- -0.479			
			M80- -0.481			
13.	Reappraisal	5	Reapp1-1.257	5	N/A	100
			Reapp2-1.715		N/A	
			Reapp3-2.407		N/A	
			Reapp4-1.674		N/A	
			Reapp5-1.441		N/A	
14.	Suppression	5	Supp1-1.238	5	N/A	100
			Supp2-1.288		N/A	
			Supp3-1.443		N/A	
			Supp4-1.548		N/A	
			Supp5-1.484		N/A	

During the scale purification of every variable, the discrimination index of the items from the original scale was estimated. Items were retained in the purified tool, based on the descending order of their discrimination indices and comparing with the list of retained items as per the classical test theory for the sake of congruence between the two approaches. Except, for the variables academic delay of gratification (item 5 and item 9) and self efficacy (item 15), there was the expected congruency, that is, items retained or purified through classical test theory were also the ones purified through item response theory. Over all, 59 out of the total 62 retained items **(95.161 %)**, displayed consistency between their CTT and IRT based estimates during scale purification. The three identified non-congruent items were removed from final data analysis.

Item Characteristic Curve (ICC), Item Information Curve (ICC) and Test Information Function Curve (TIC) of the Retained Items of the Fourteen SRL Variables:

1. **Scale One - Critical Thinking:**

   Item Discrimination Report:

```
Call:
grm(data = CT_Copy, constrained = FALSE)

Coefficients:
     Extrmt1  Extrmt2  Extrmt3  Extrmt4  Extrmt5  Extrmt6  Dscrmn
M47   -2.903   -2.190   -1.372   -0.360    0.631    1.749   1.529
M51   -2.874   -2.063   -1.302   -0.395    0.531    1.416   1.728
M66   -2.950   -2.102   -1.374   -0.372    0.564    1.580   1.513
M71   -2.888   -2.159   -1.424   -0.505    0.558    1.542   1.720

Log.Lik: -11909.3

> fit1 <- grm(CT, constrained = FALSE)
> fit1

Call:
grm(data = CT, constrained = FALSE)

Coefficients:
     Extrmt1  Extrmt2  Extrmt3  Extrmt4  Extrmt5  Extrmt6  Dscrmn
M38   -3.110   -2.199   -1.406   -0.294    0.856    1.826   1.296
M47   -2.827   -2.138   -1.345   -0.356    0.614    1.709   1.597
M51   -2.938   -2.100   -1.323   -0.399    0.542    1.448   1.652
M66   -2.907   -2.068   -1.348   -0.362    0.559    1.563   1.547
M71   -2.911   -2.173   -1.430   -0.507    0.563    1.557   1.691

Log.Lik: -14869.99
```

Figure 4.69 Critical Thinking – Item Discrimination Report

Item Characterictic Curves (ICC):

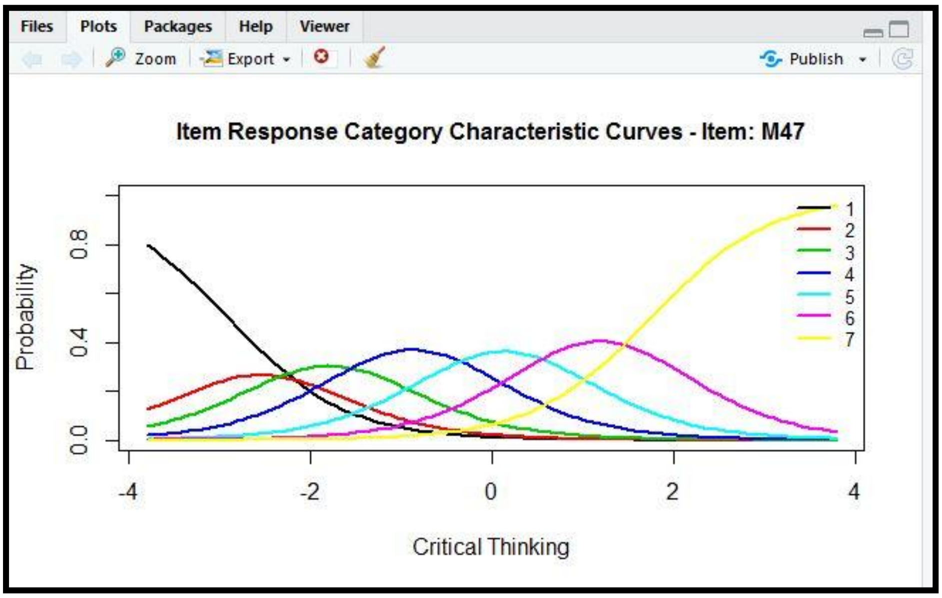


Figure 4.70 **ICC- M47 Item**

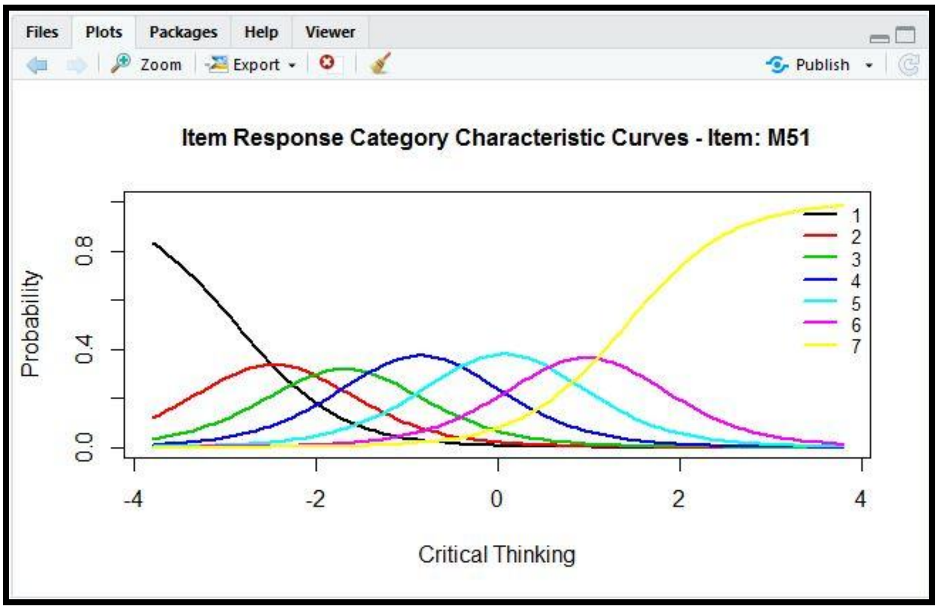


Figure 4.71 **ICC- M51 Item**

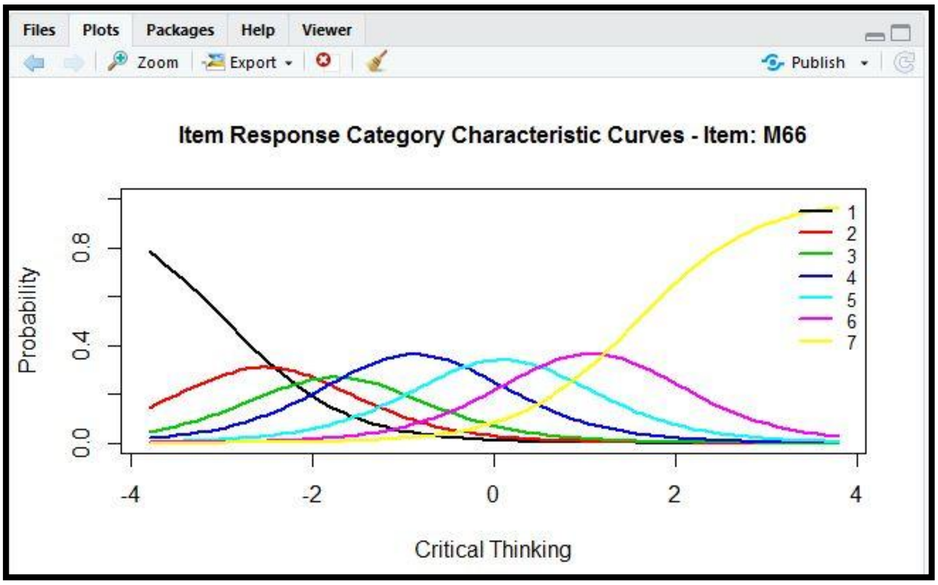


Figure 4.72 **ICC- M66 Item**

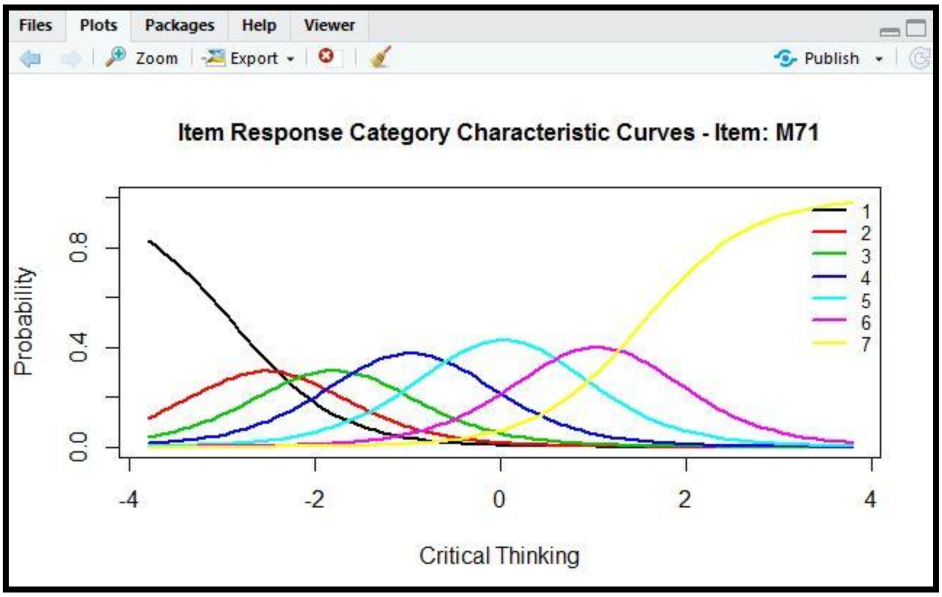


Figure 4.73 **ICC- M71 Item**

Option Characteristic Curves (OCC) using mirt function:

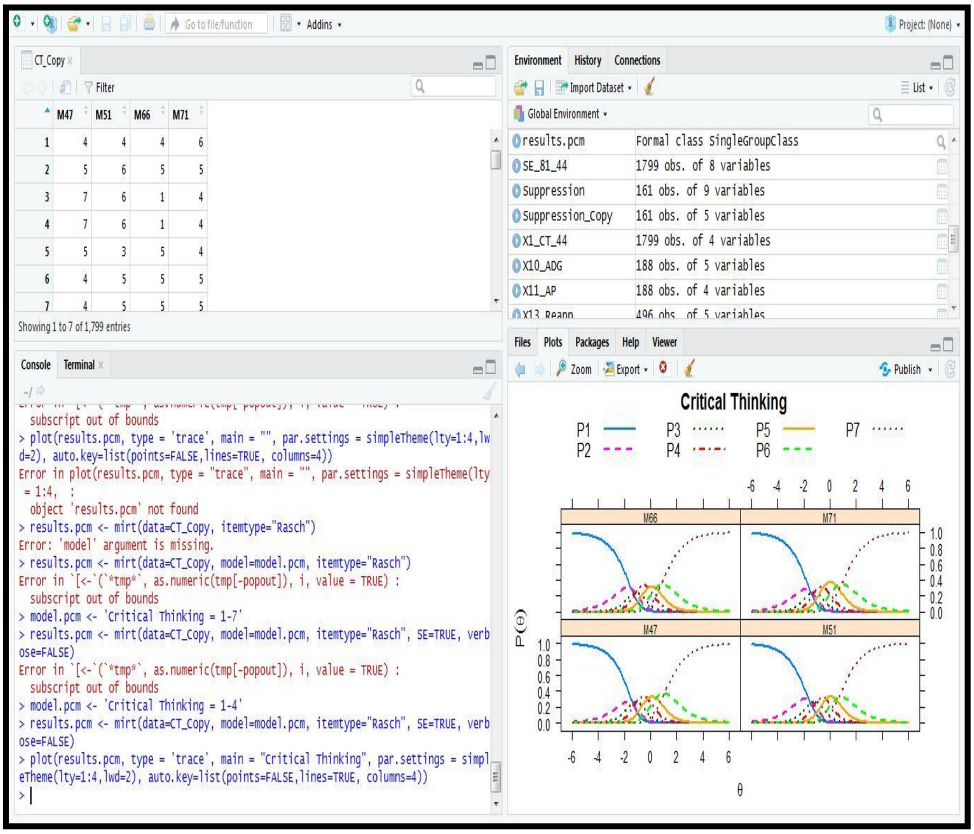


Figure 4.74 **Option Characteristic Curves (OCC) – Critical Thinking**

Item Information Curve (IIC) using ltm and psych functions:

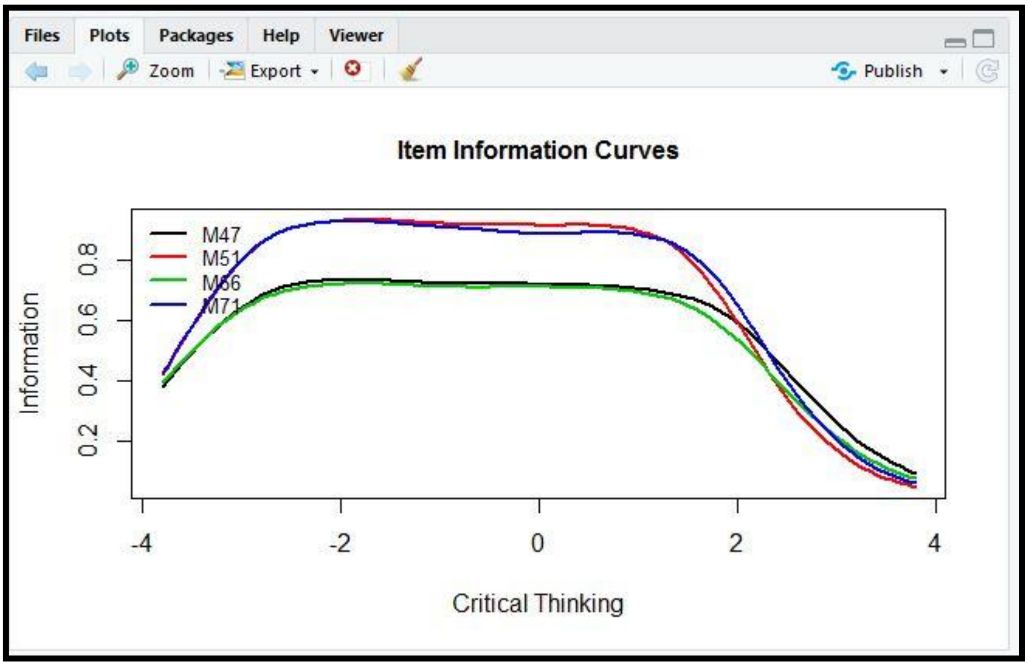


Figure 4.75 **Item Information Curve (IIC) – Critical Thinking**

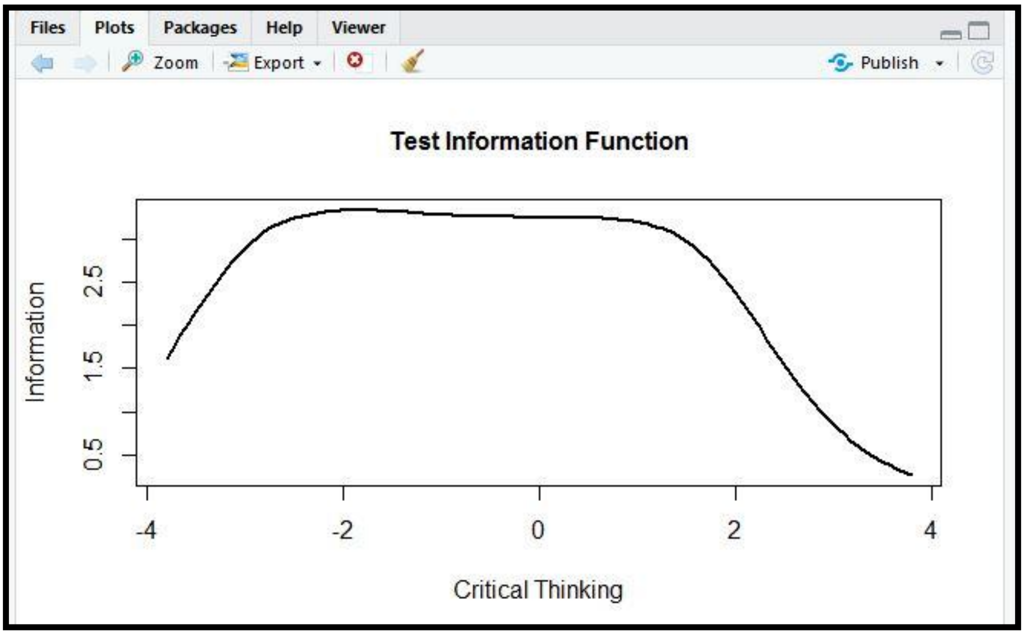


Figure 4.76 **Test Information Curve (ICC) – Critical Thinking**

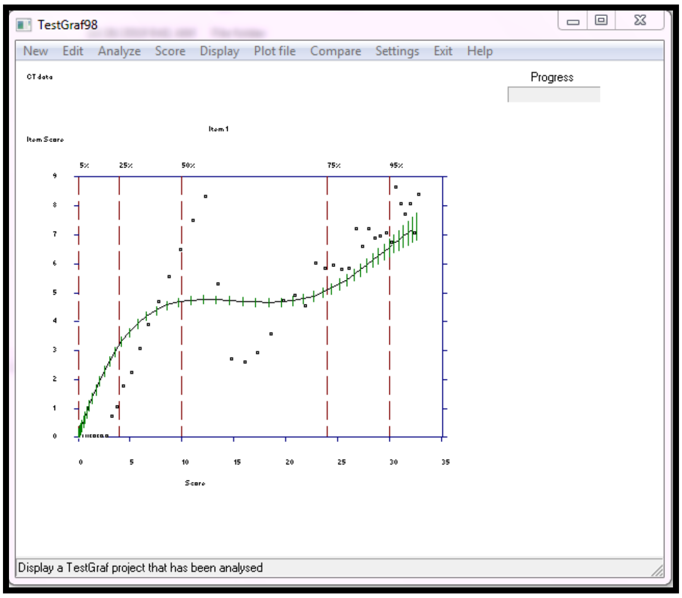
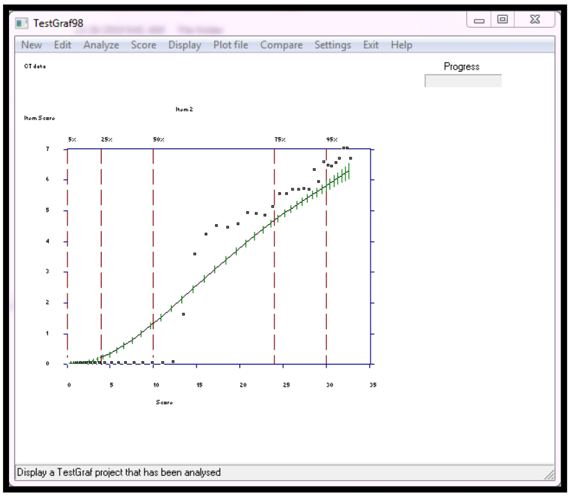
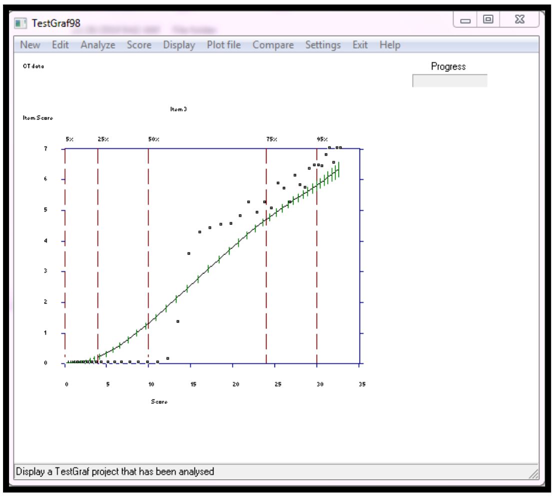


Figure 4.77 **Non Parametric Item Characteristic Curves (ICC) of Critical Thinking Items using TestGraf98:**





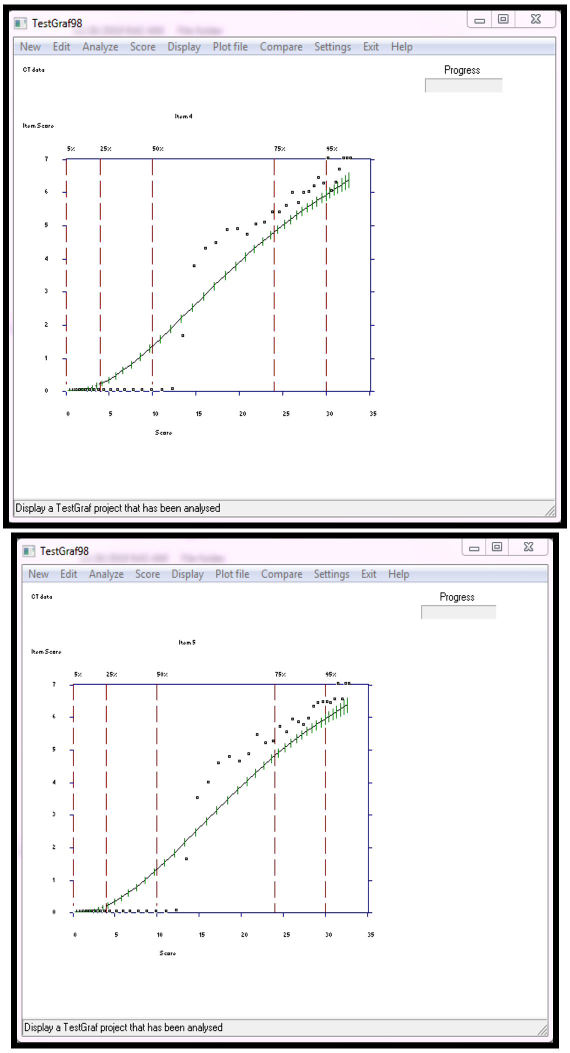
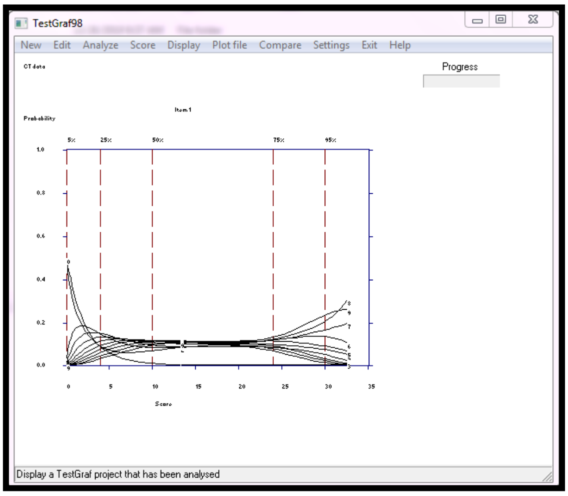
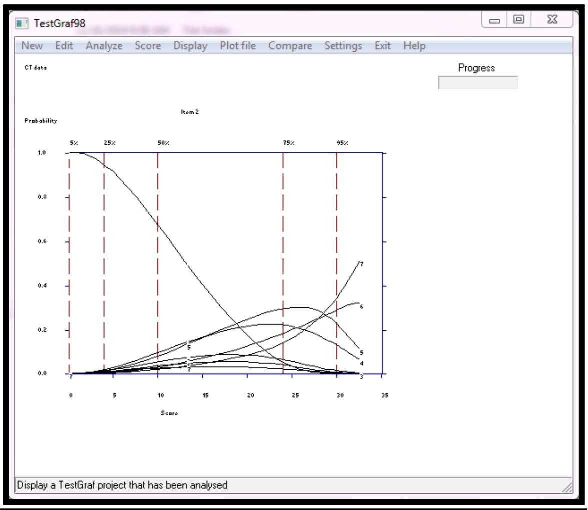
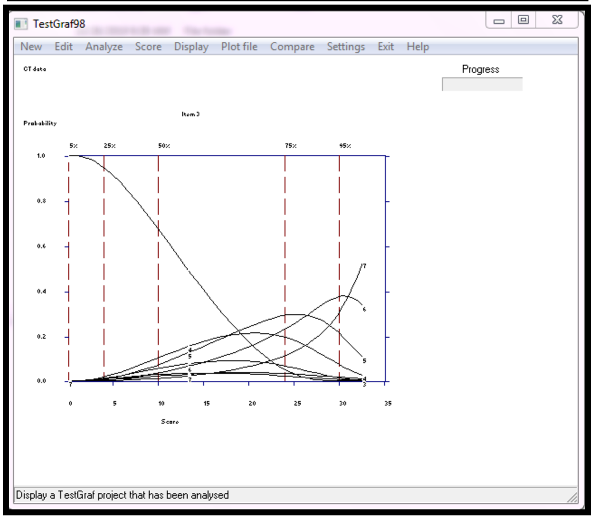


Figure 4.78 **Non Parametric Item Characteristic Curves (ICC) of Rest of Critical Thinking Items**

Interpretation: Expect the first item, rest of all the items show monotinicity as the ICC is increasing with ability, thus satisfying the vital assumption of Non-parametric item response theory.


TestGraf98
New Edit Analyze Score Display Plot file Compare Settings Exit Help
Progress
Item 1
Probability
Score
Display a TestGraf project that has been analysed


TestGraf98
New Edit Analyze Score Display Plot file Compare Settings Exit Help
Progress
Item 2
Probability
Score
Display a TestGraf project that has been analysed


TestGraf98
New Edit Analyze Score Display Plot file Compare Settings Exit Help
Progress
Item 3
Probability
Score
Display a TestGraf project that has been analysed

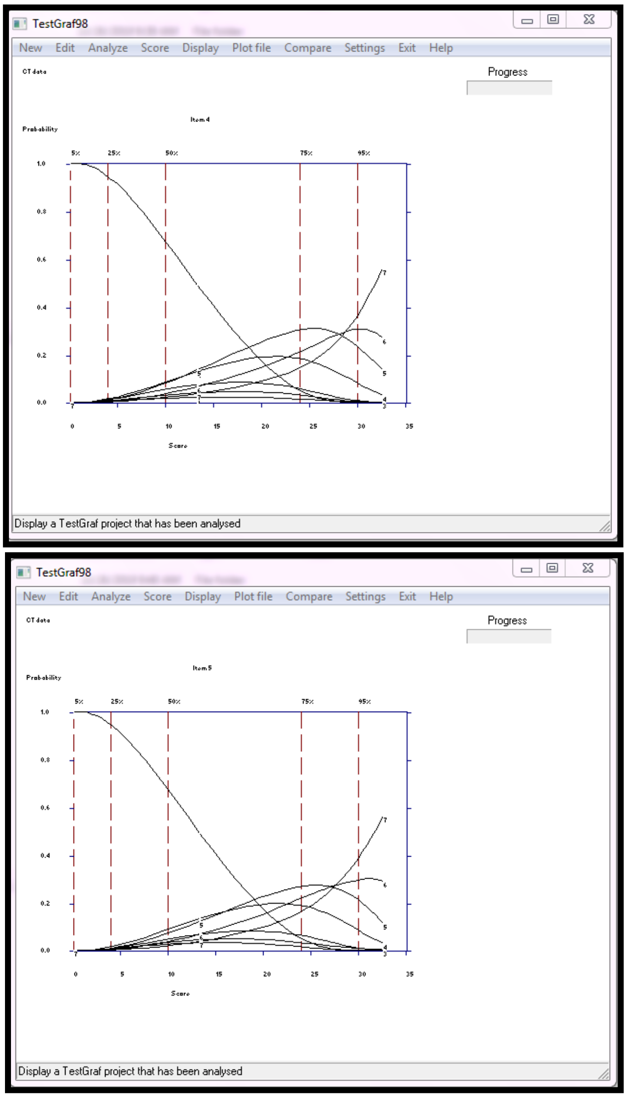


Figure 4.79 **Non Parametric Option Characteristic Curves (OCC) of Critical Thinking Items using TestGraf98**

2. Scale Two – Organization:

The performance of the items and their options of Organization scale, in measuring its presence at different levels in the subjects is assessed below:

Item Discrimination Report:

```
> library(haven)
> Org <- read_sav("D:/MI in R/MLSQ/Org.sav")
> View(Org)
> fit1 <- grm(Org, constrained = FALSE)
> fit1

Call:
grm(data = Org, constrained = FALSE)

Coefficients:
     Extrmt1  Extrmt2  Extrmt3  Extrmt4  Extrmt5  Extrmt6  Dscrmn
M32   -2.938   -2.230   -1.493   -0.598    0.342    1.296   1.479
M42   -2.823   -2.136   -1.418   -0.549    0.247    1.104   1.707
M49   -2.595   -2.003   -1.343   -0.496    0.338    1.345   1.466
M63   -2.940   -2.263   -1.418   -0.581    0.279    1.206   1.650

Log.Lik: -12077.39
```

Figure 4.80 **Item Discrimination Report – Organization**

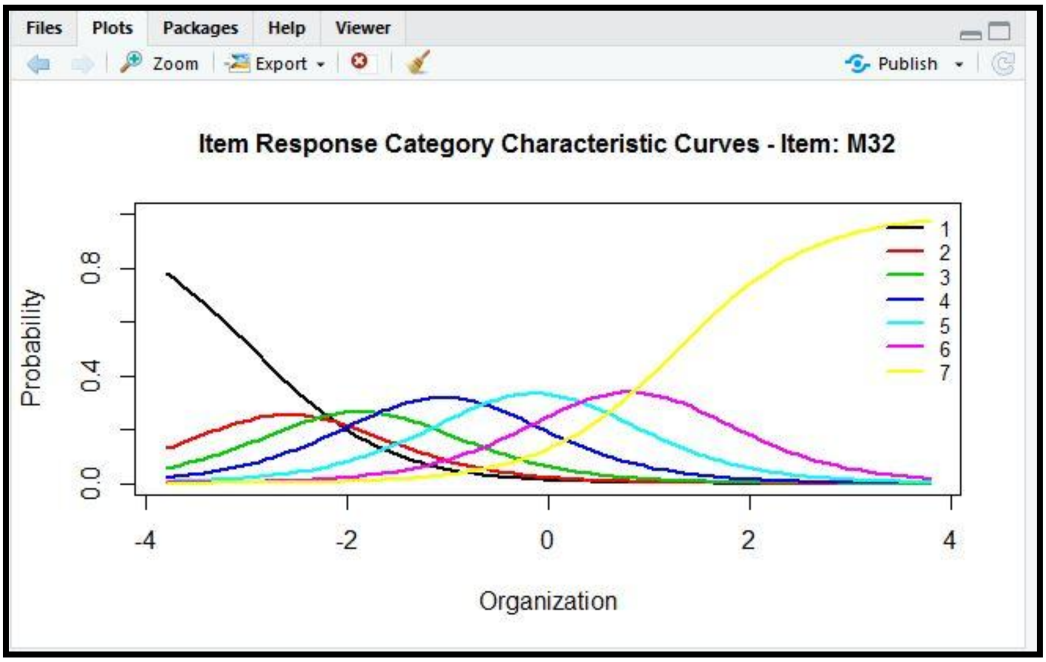


Figure 4.81 **Item Characteristic Curves (ICC) – M32**

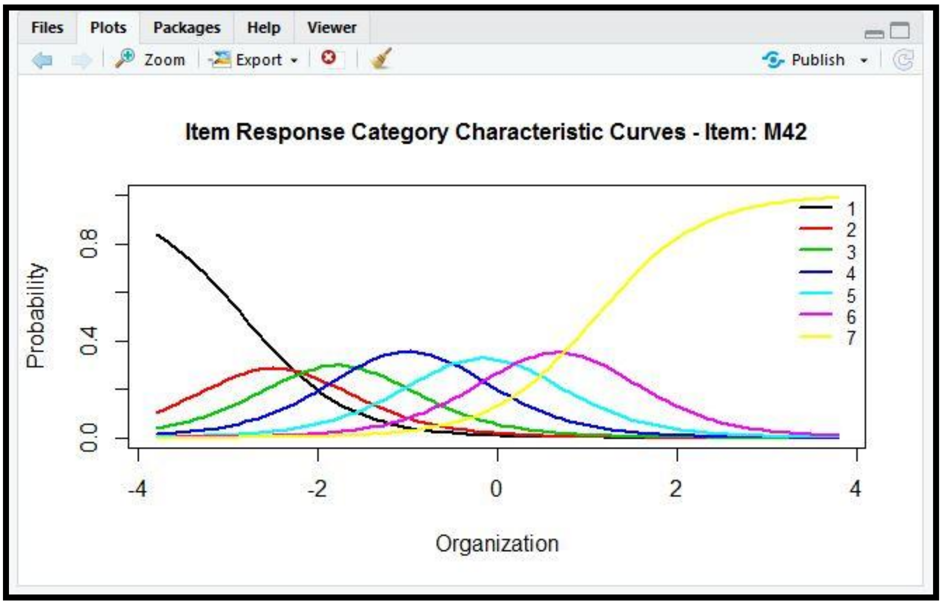


Figure 4.82 **Item Characteristic Curves (ICC) – M42**

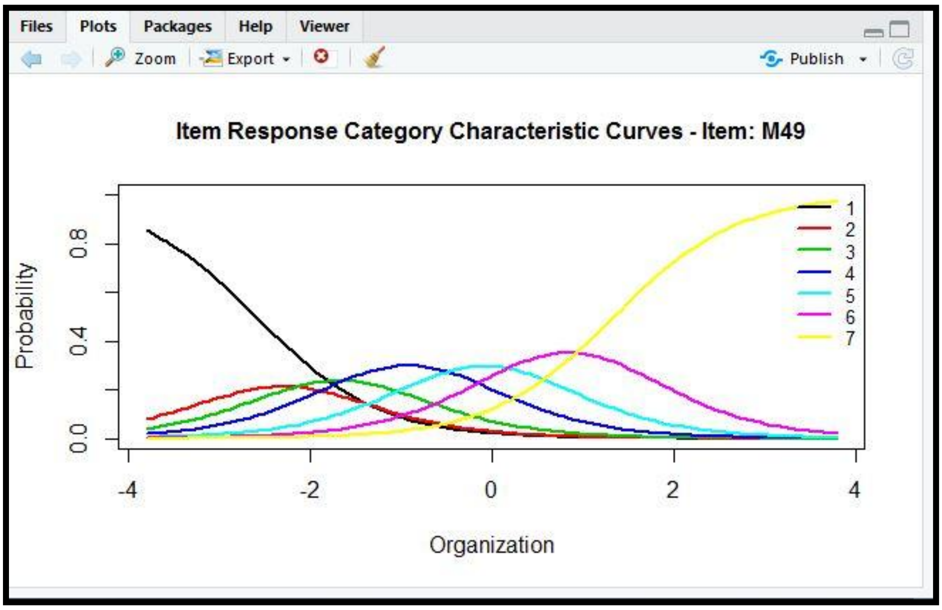


Figure 4.83 **Item Characteristic Curves (ICC) – M49**

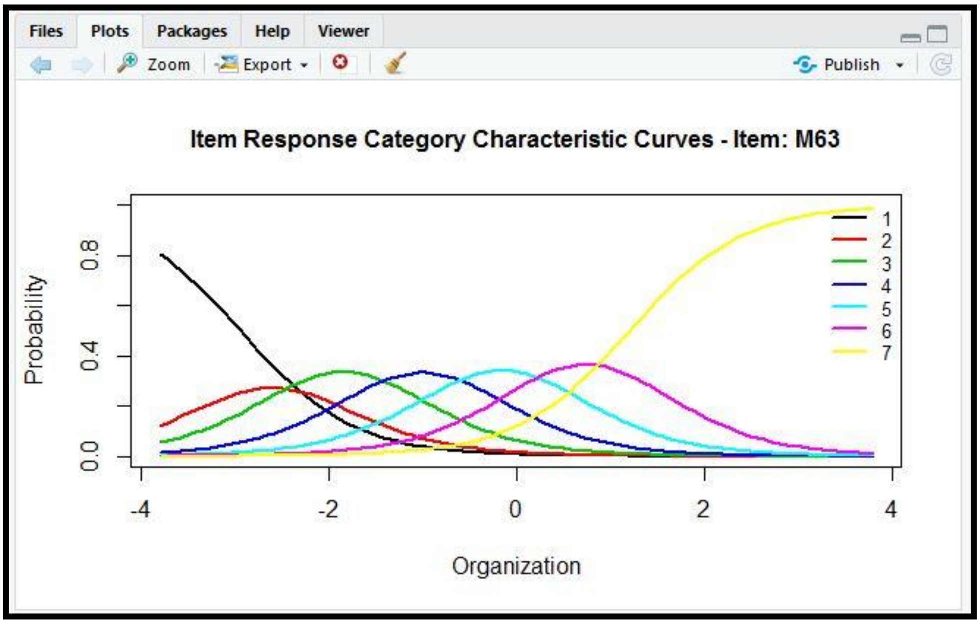


Figure 4.84 **Item Characteristic Curves (ICC) – M63**

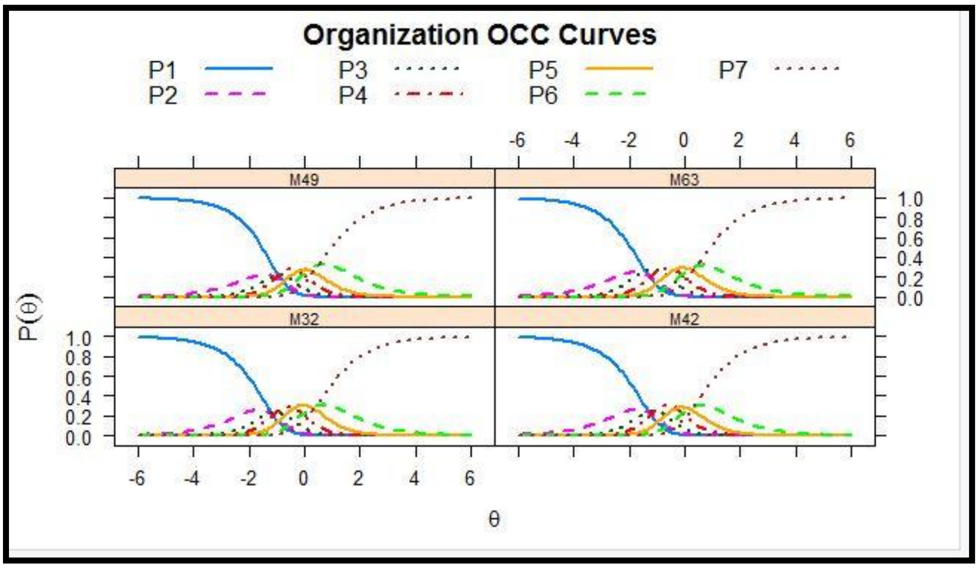


Figure 4.85 **Option Characteristic Curves – Organization**

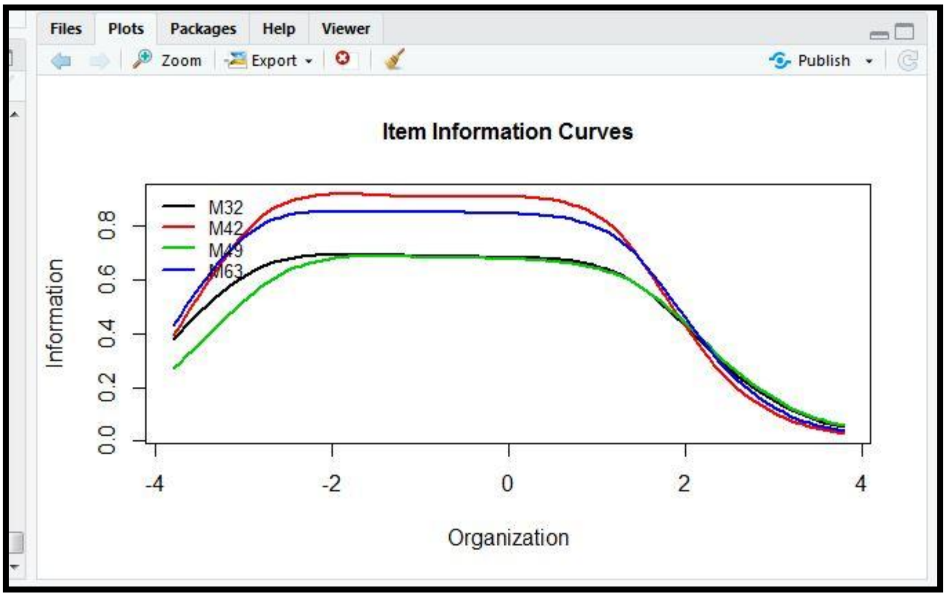


Figure 4.86 **Item Information Curve (IIC) – Organization**

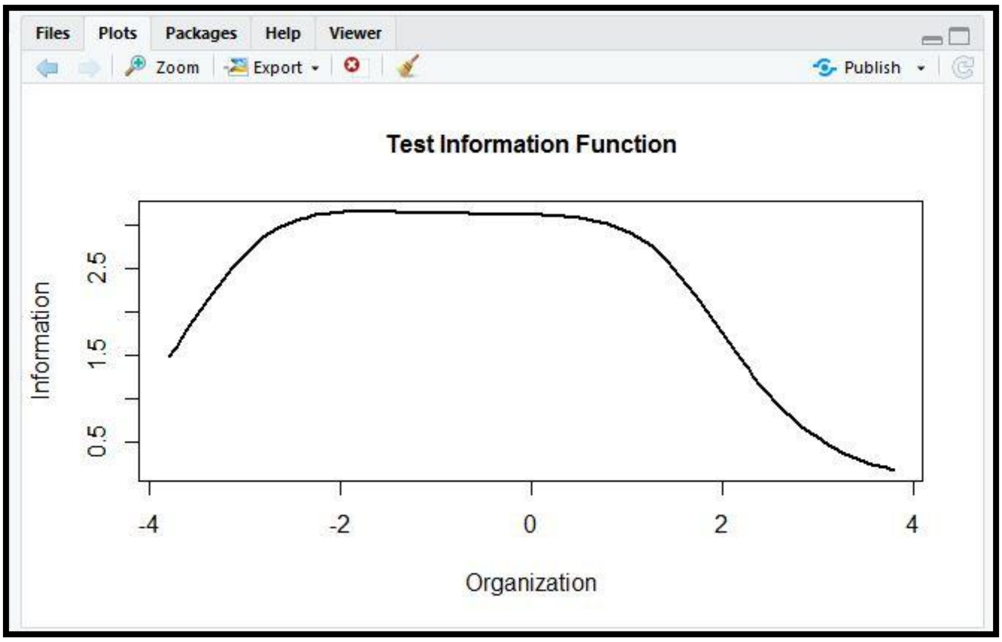


Figure 4.87 **Test Information Curve (TIC) - Organization**

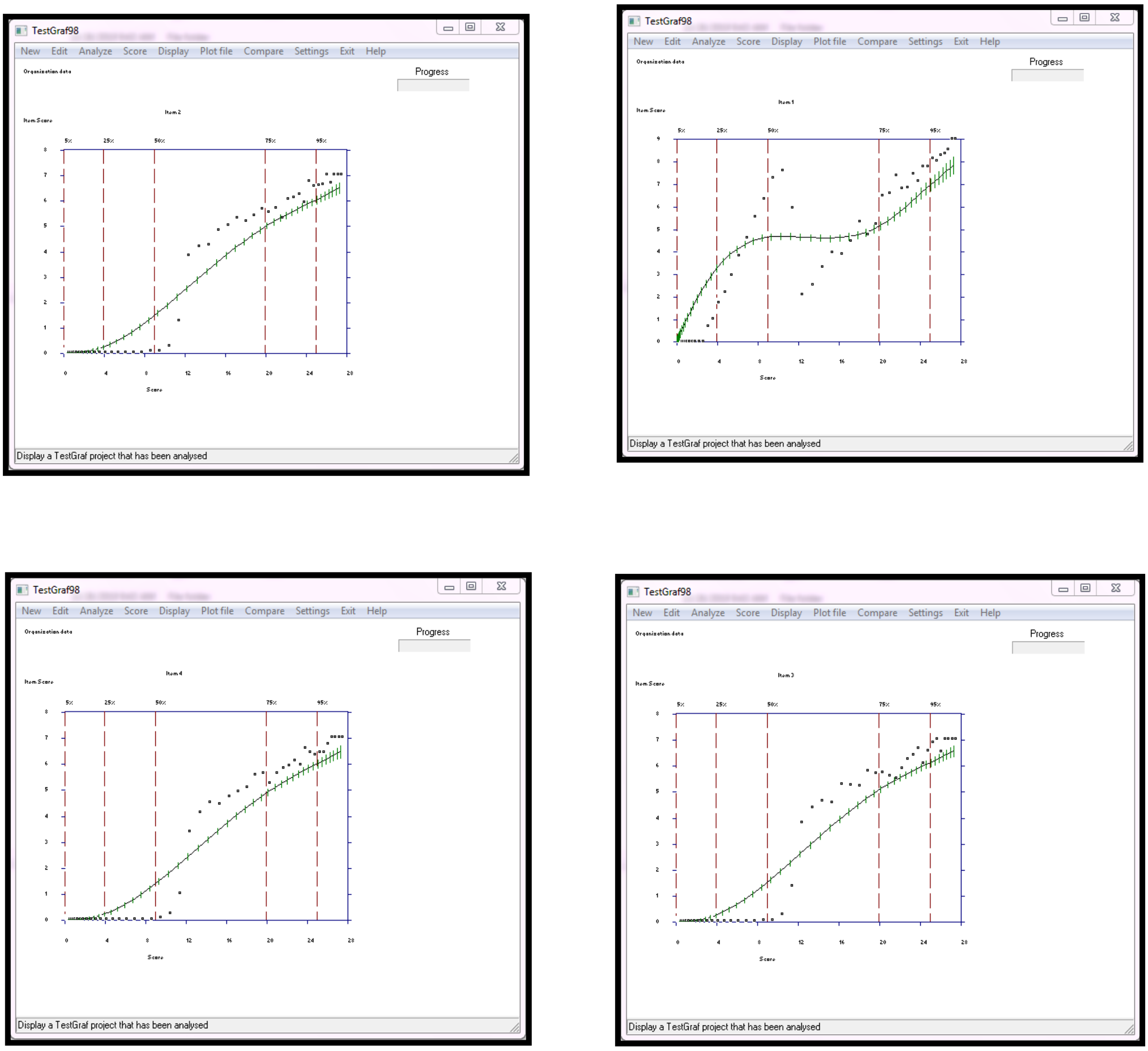


Figure 4.88 **Non Parametric Item Characteristic Curves (ICC) of Organization Items using TestGraf98:**

Interpretation: Except thefirst item**,** rest of the three items are monotonous as desired.

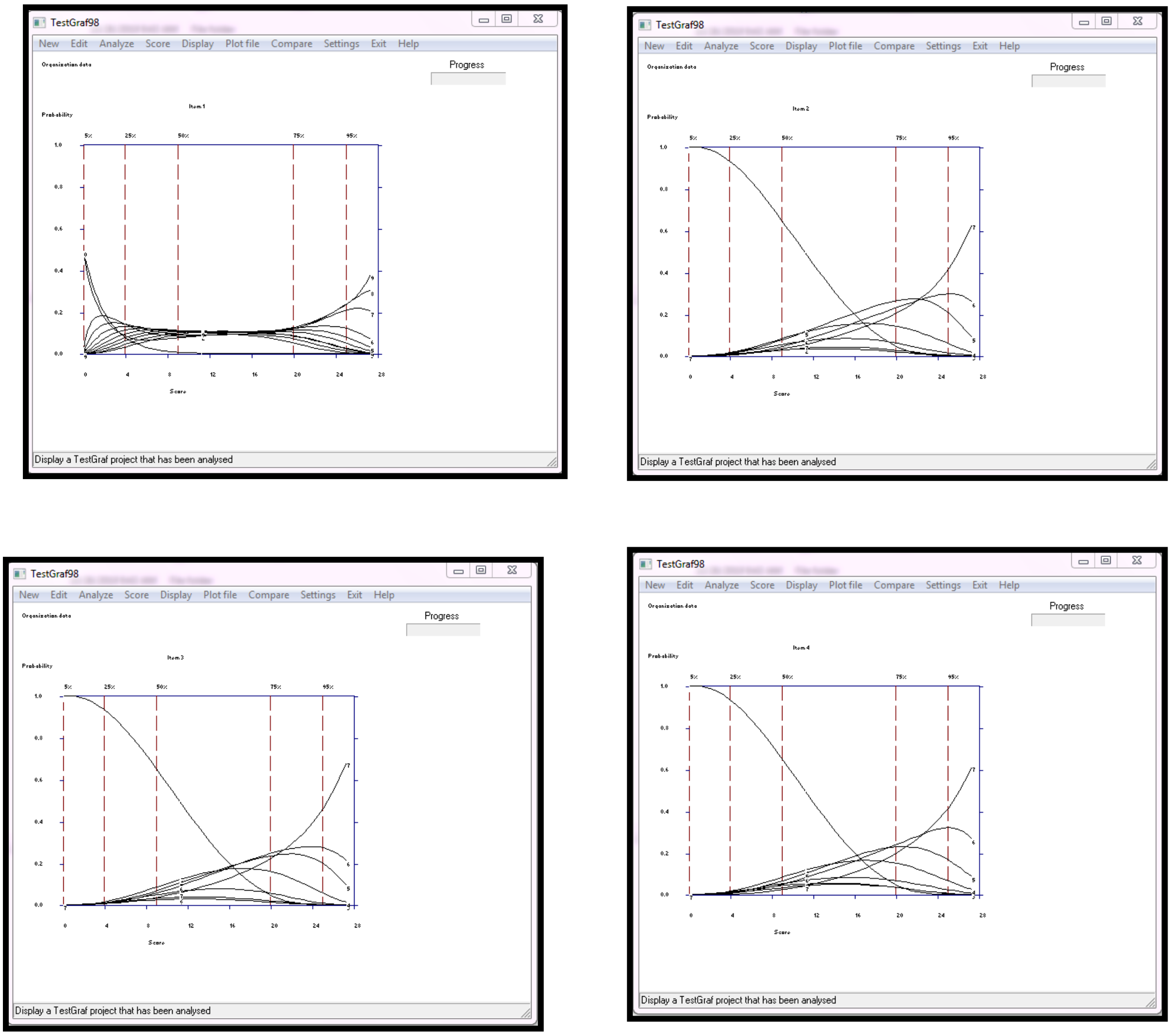


Figure 4.89 **Non Parametric Option Characteristic Curves (OCC) Organization Items using TestGraf98:**

3. Scale Three – Planning:

The performance of the items and their options of Planning scale, in measuring its presence at different levels in the subjects is assessed below:

```
Call:
grm(data = Planning_Data, constrained = FALSE)

Coefficients:
       Extrmt1  Extrmt2  Extrmt3  Extrmt4  Dscrmn
Plan1   -2.973   -1.033    1.052    2.932   0.897
Plan2   -2.012   -1.005   -0.189    0.659   2.160
Plan3   -1.399   -0.673   -0.092    0.877   3.743
Plan4   -2.052   -0.939    0.401    1.923   1.411
Plan5   -1.672   -0.880    0.034    0.929   2.000
Plan6   -1.739   -0.942   -0.013    1.019   1.464
Plan7   -1.993   -0.730    0.418    1.337   1.580

Log.Lik: -995.031

> fit2 <- grm(Planning_Data_Copy, constrained = FALSE)
> fit2

Call:
grm(data = Planning_Data_Copy, constrained = FALSE)

Coefficients:
       Extrmt1  Extrmt2  Extrmt3  Extrmt4  Dscrmn
Plan2   -2.058   -1.048   -0.206    0.664   2.120
Plan3   -1.522   -0.730   -0.090    0.949   3.072
Plan5   -1.669   -0.879    0.033    0.915   2.120

Log.Lik: -430.238
```

Figure 4.90 **Item Discrimination Report - Planning**

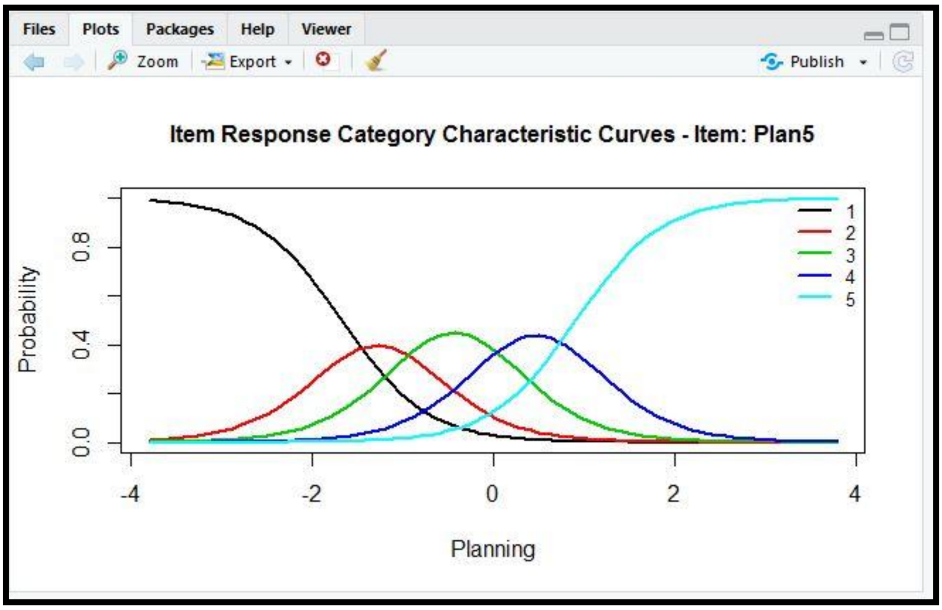


Figure 4.91 **Item Characteristic Curves (ICC) – Plan5**

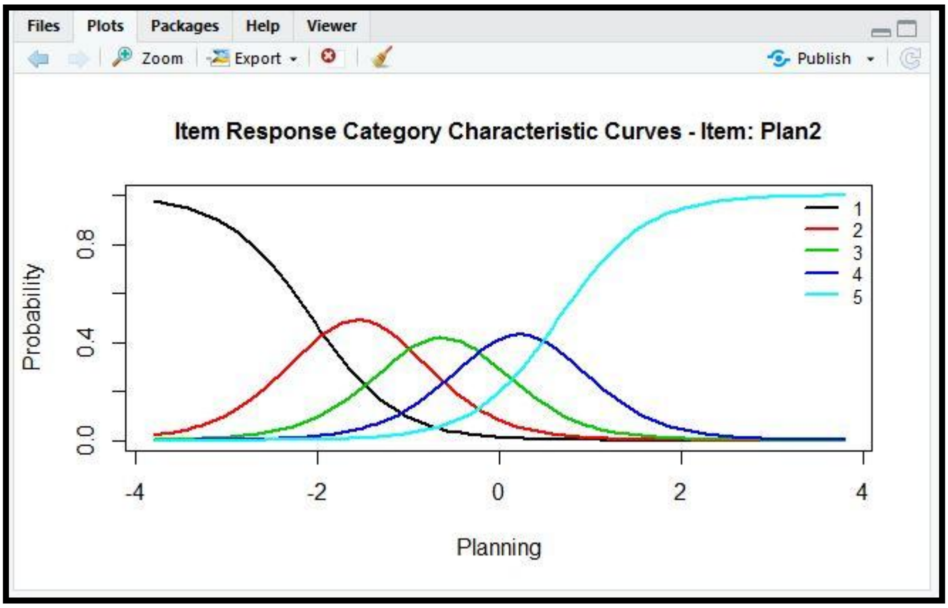


Figure 4.92 **Item Characteristic Curves (ICC) – Plan2**

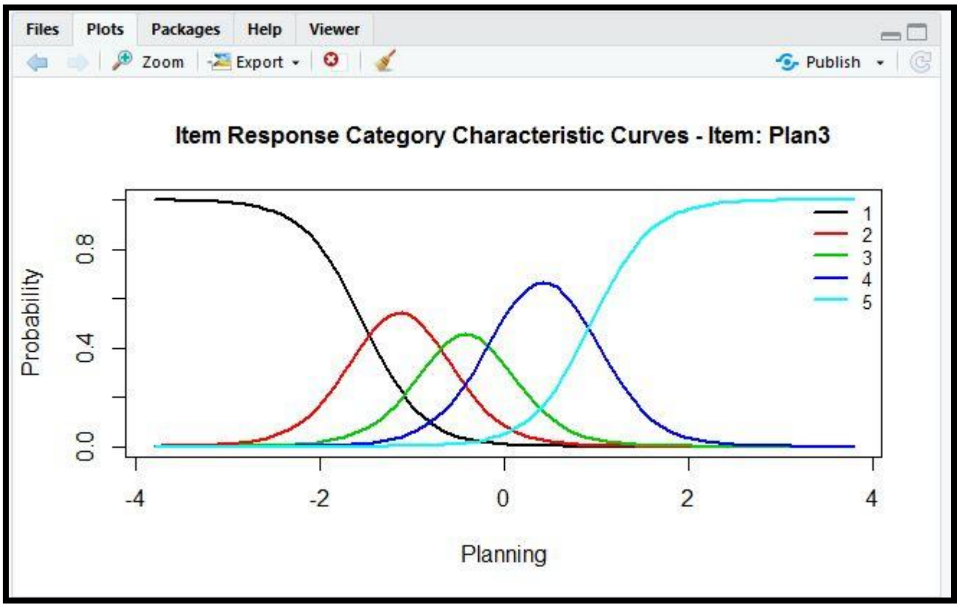


Figure 4.93 **Item Characteristic Curves (ICC) – Plan3**

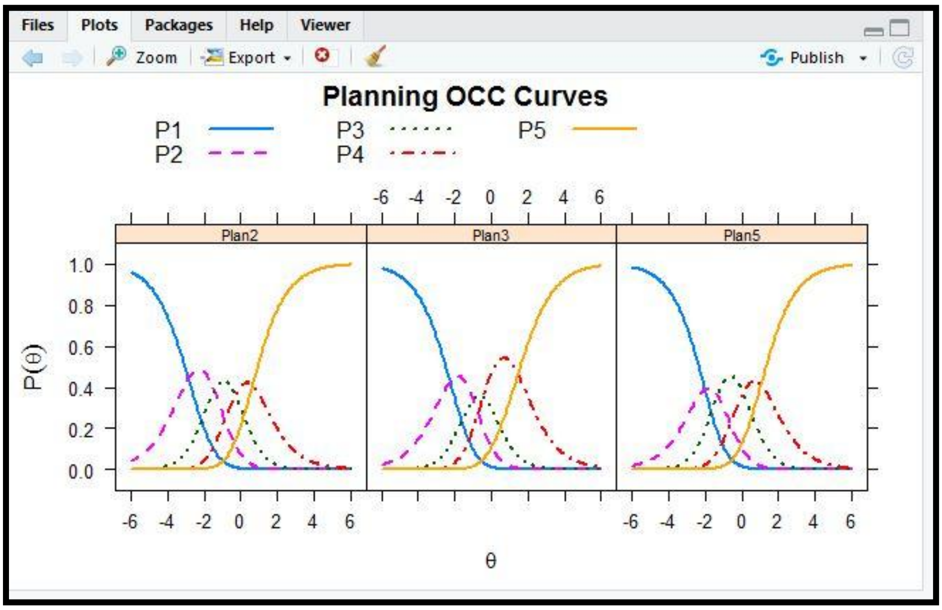


Figure 4.94 **Option Characteristic Curves (OCC) - Planning**

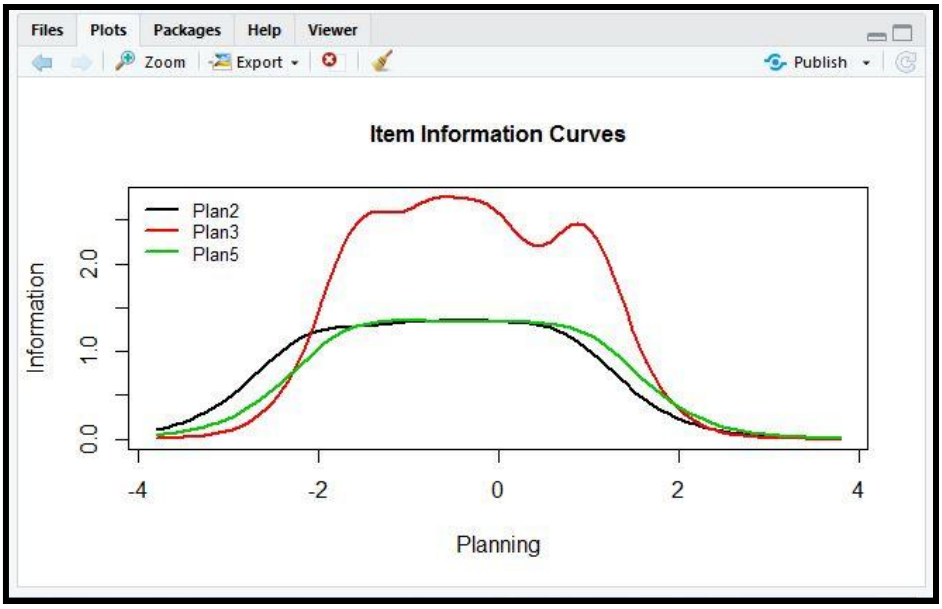


Figure 4.95 **Item Information Curve (IIC) - Planning**

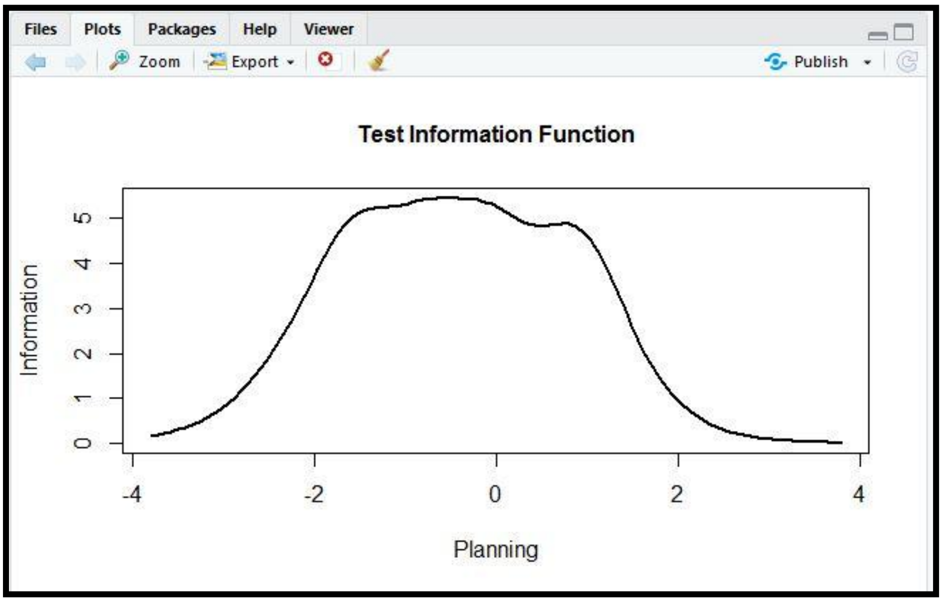
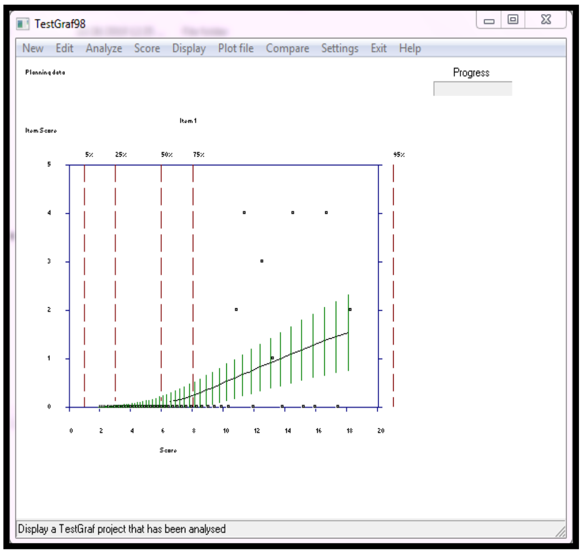
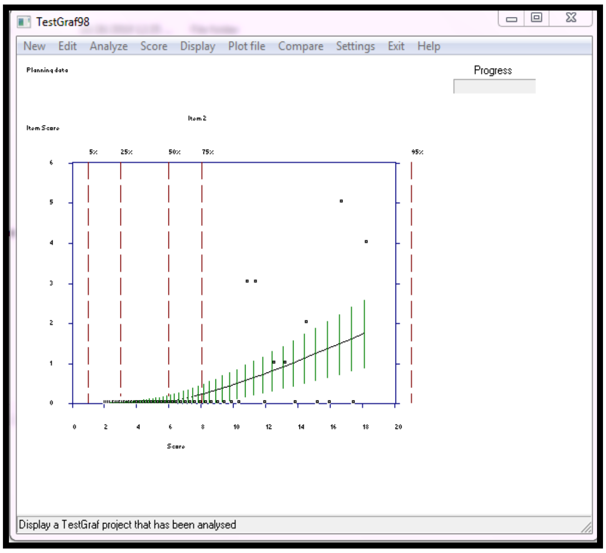
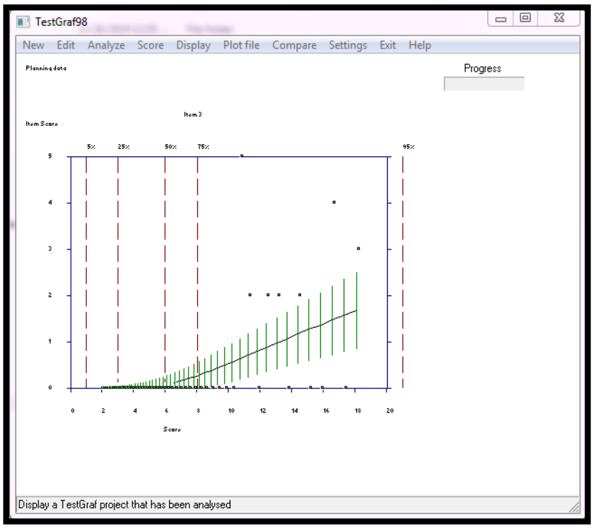
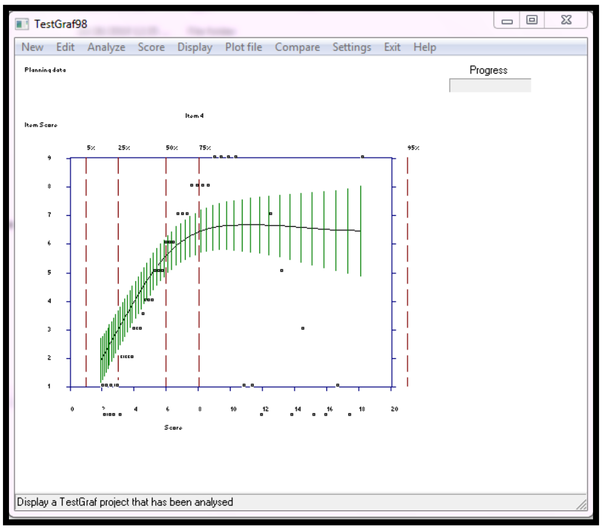


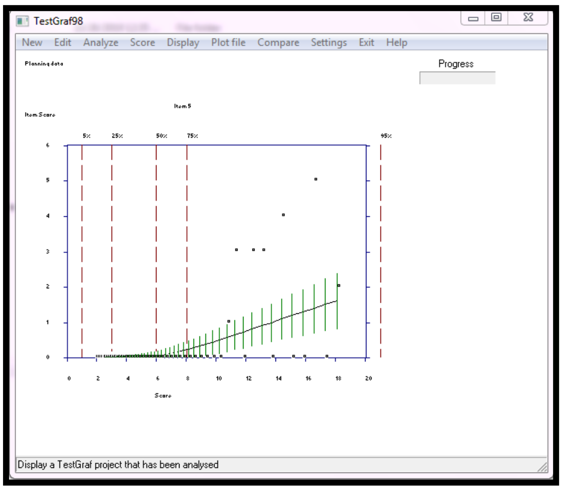
Figure 4.96 **Test Information Curve (TIC) – Planning**


TestGraf98
New Edit Analyze Score Display Plot file Compare Settings Exit Help
Progress
Display a TestGraf project that has been analysed


TestGraf98
New Edit Analyze Score Display Plot file Compare Settings Exit Help
Progress
Display a TestGraf project that has been analysed


TestGraf98
New Edit Analyze Score Display Plot file Compare Settings Exit Help
Progress
Display a TestGraf project that has been analysed


TestGraf98
New Edit Analyze Score Display Plot file Compare Settings Exit Help
Progress
Display a TestGraf project that has been analysed


TestGraf98
New Edit Analyze Score Display Plot file Compare Settings Exit Help
Progress
Display a TestGraf project that has been analysed

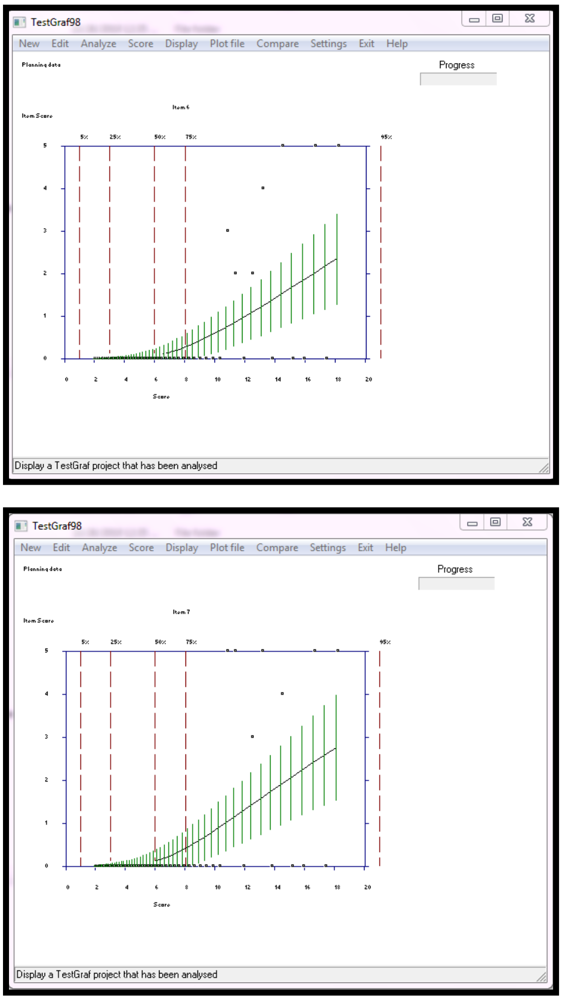
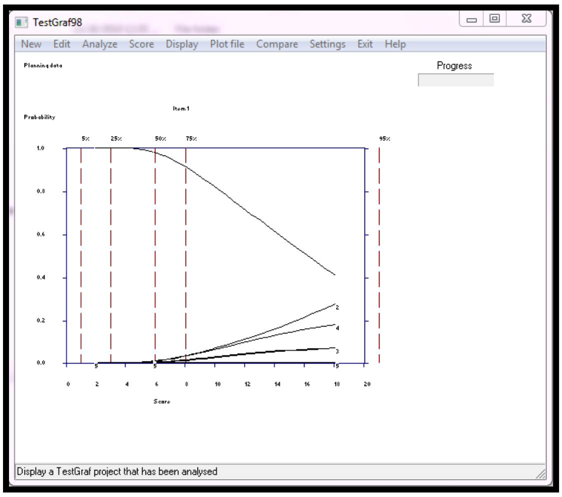
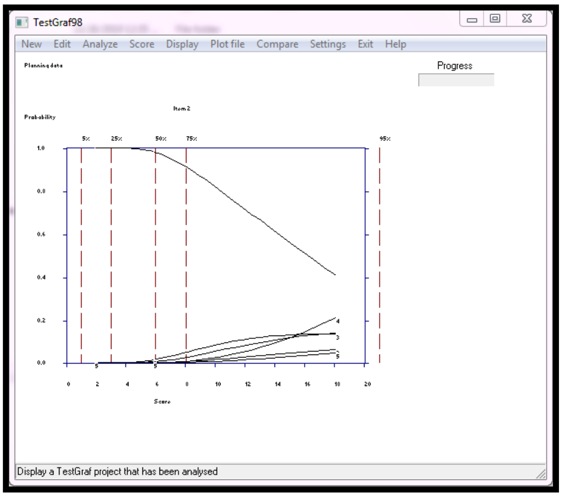
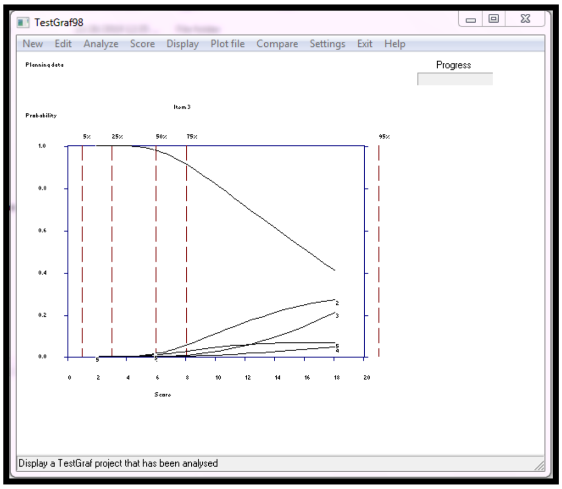


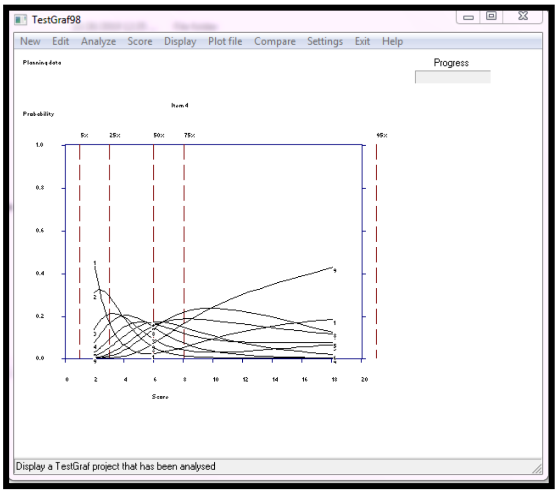
Figure 4.97 **Non Parametric Item Characteristic Curves (ICC) Planning Items using TestGraf98**

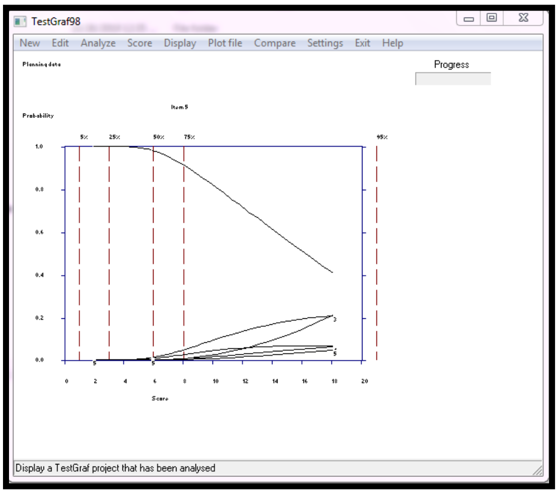
Interpretation: The ICC of item4 stands out to be an exception as it does not satisfy the assumption of montonicity and is to be deleted as indicated by non-parametric item response theory.

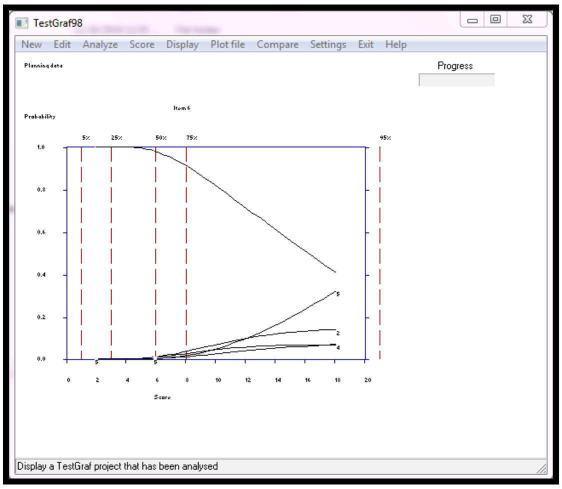

TestGraf98
New Edit Analyze Score Display Plot file Compare Settings Exit Help
Planning data
Progress
Item 1
Probability
Score
Display a TestGraf project that has been analysed


TestGraf98
New Edit Analyze Score Display Plot file Compare Settings Exit Help
Planning data
Progress
Item 2
Probability
Score
Display a TestGraf project that has been analysed


TestGraf98
New Edit Analyze Score Display Plot file Compare Settings Exit Help
Planning data
Progress
Item 3
Probability
Score
Display a TestGraf project that has been analysed


TestGraf98
New Edit Analyze Score Display Plot file Compare Settings Exit Help
Planning data
Progress
Item 4
Probability
Score
Display a TestGraf project that has been analysed


TestGraf98
New Edit Analyze Score Display Plot file Compare Settings Exit Help
Planning data
Progress
Item 5
Probability
Score
Display a TestGraf project that has been analysed



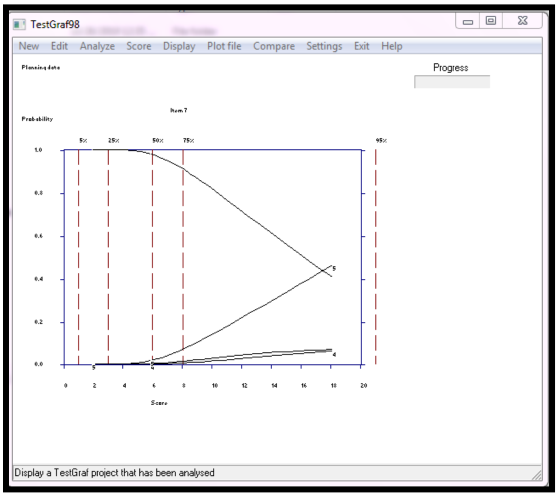


Figure 4.98 **Non Parametric Option Characteristic Curves (OCC) Planning Items using TestGraf98:**

4. Items / Options Performance of Scale Four – Self Recording:

```
Call:
grm(data = Self_Recording_Data, constrained = FALSE)

Coefficients:
$Srec8
Extrmt1  Extrmt2  Extrmt3  Extrmt4   Dscrmn
 -2.087   -1.047    0.045    1.586    1.330

$Srec9
Extrmt1  Extrmt2  Extrmt3  Extrmt4   Dscrmn
 -3.122   -1.441   -0.061    1.931    0.958

$Srec10
Extrmt1  Extrmt2  Extrmt3  Extrmt4   Dscrmn
 -2.326   -1.201    0.359    1.627    1.518

$Srec11
Extrmt1  Extrmt2  Extrmt3  Extrmt4   Dscrmn
 -2.083   -0.662    0.279    1.160    2.128

$Srec12
Extrmt1  Extrmt2  Extrmt3  Extrmt4   Dscrmn
 -1.930   -1.025    0.210    1.245    1.740

$Srec13
Extrmt1  Extrmt2  Extrmt3  Extrmt4   Dscrmn
 -2.283   -0.830    0.859    2.531    1.171

$Srec14
Extrmt1  Extrmt2  Extrmt3  Extrmt4   Dscrmn
 -1.998   -0.887   -0.058    1.192    1.891

$Gender
Extrmt1   Dscrmn
-35.085    0.133


Log.Lik: -1016.543
```

Figure 4.99 **Item Discrimination Report – Self Recording – Original Scale**

```
Log.Lik: -1016.543

> fit2 <- grm(Self_Recording_Data_Copy, constrained = FALSE)
> fit2

Call:
grm(data = Self_Recording_Data_Copy, constrained = FALSE)

Coefficients:
$Srec10
Extrmt1  Extrmt2  Extrmt3  Extrmt4   Dscrmn
 -2.378   -1.210    0.373    1.642    1.473

$Srec11
Extrmt1  Extrmt2  Extrmt3  Extrmt4   Dscrmn
 -2.209   -0.684    0.327    1.219    1.900

$Srec12
Extrmt1  Extrmt2  Extrmt3  Extrmt4   Dscrmn
 -1.721   -0.908    0.193    1.089    2.407

$Srec14
Extrmt1  Extrmt2  Extrmt3  Extrmt4   Dscrmn
 -2.103   -0.909   -0.042    1.235    1.740

$Gender
Extrmt1   Dscrmn
-87.495    0.053


Log.Lik: -580.192
```

Figure 4.100 **Item Discrimination Report – Self Recording - Parsimonious Scale**

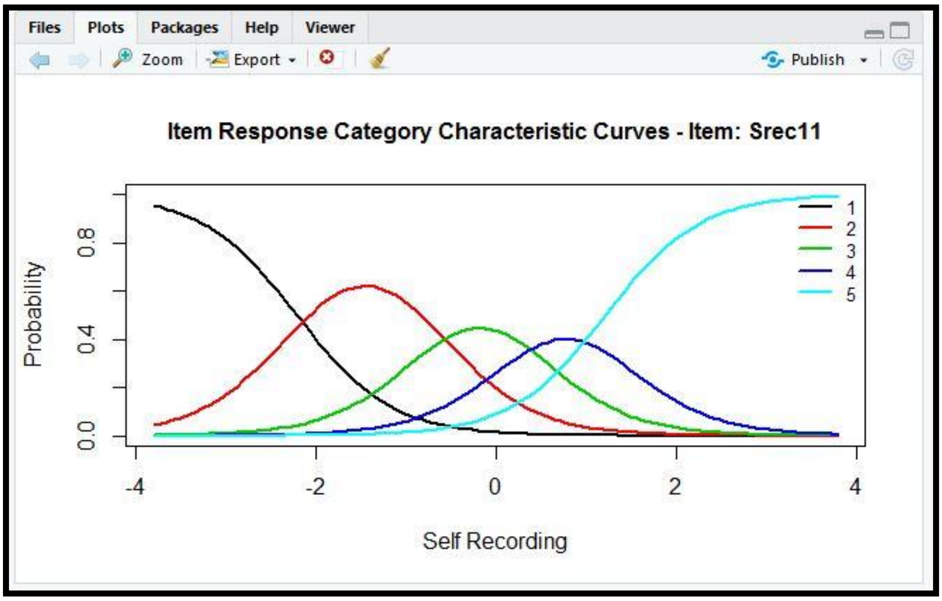


Figure 4.101 **Item Characteristic Curve (ICC) – Srec1**

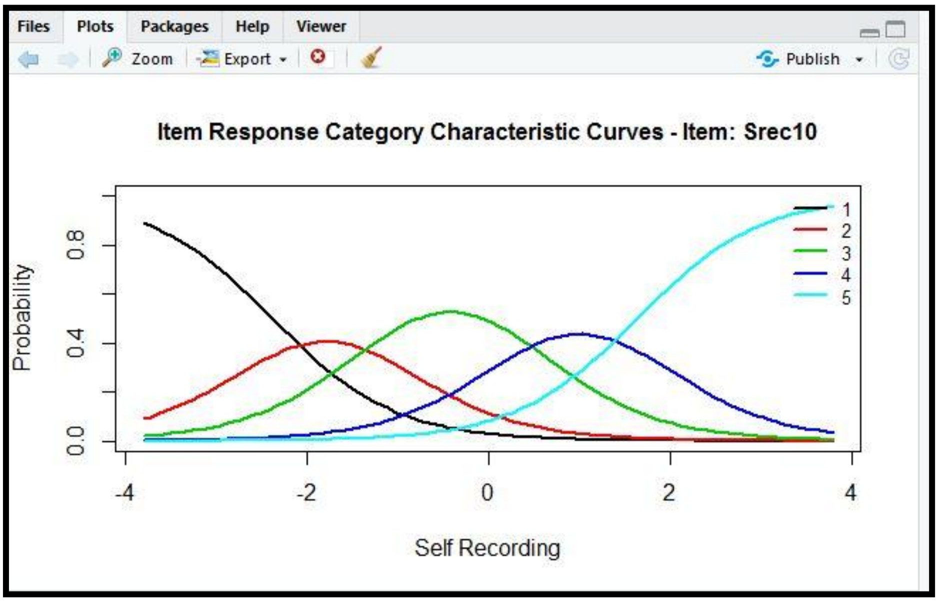


Figure 4.102 **Item Characteristic Curve (ICC) – Srec10**

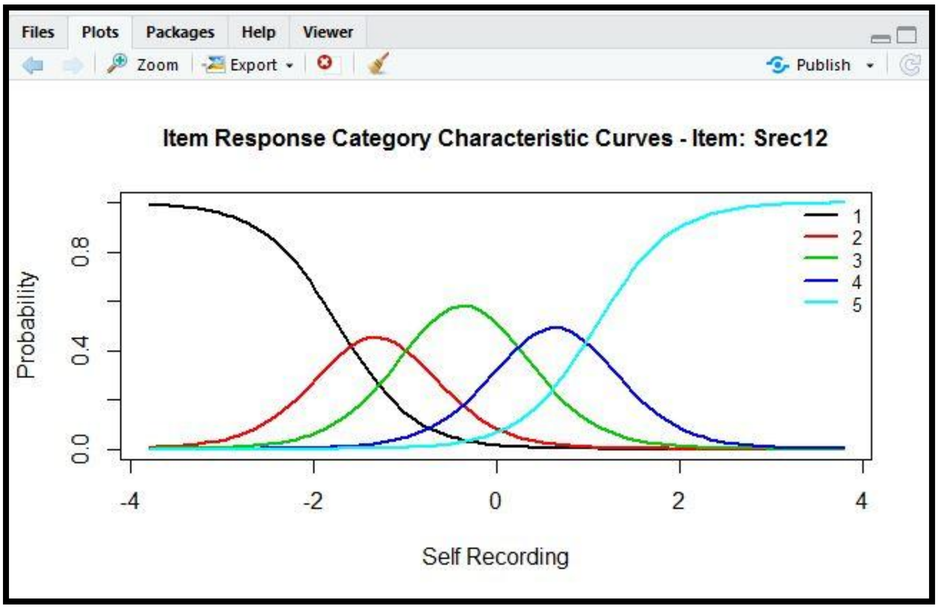


Figure 4.103 **Item Characteristic Curve (ICC) – Srec12**

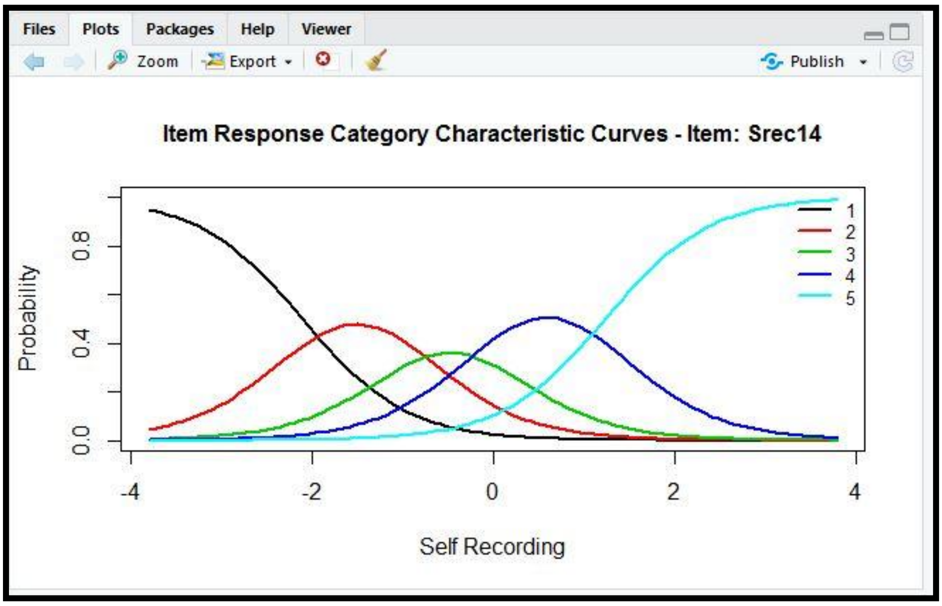


Figure 4.104 **Item Characteristic Curve (ICC) – Srec14**

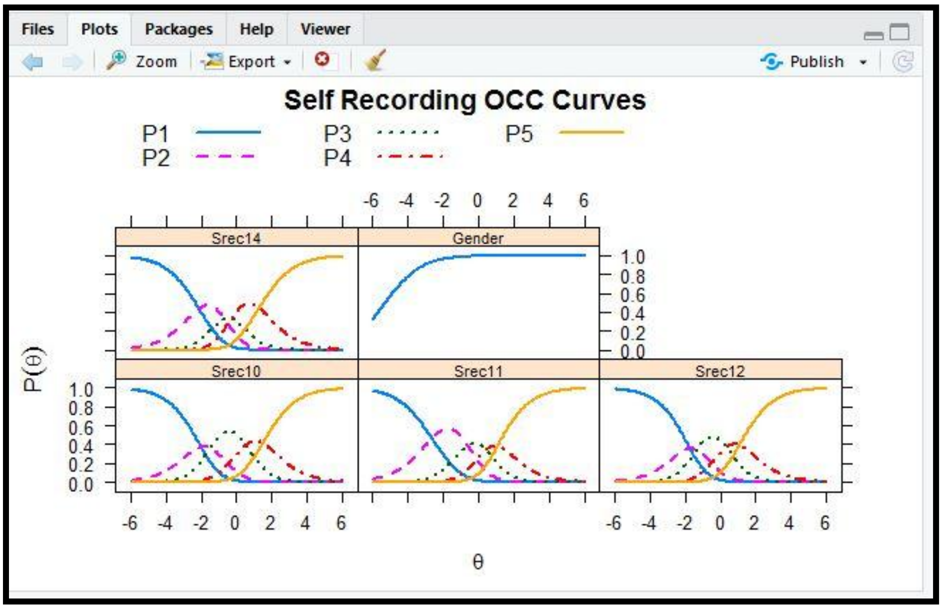


Figure 4.105 **Option Characteristic Curves (OCC) – Self Recording**

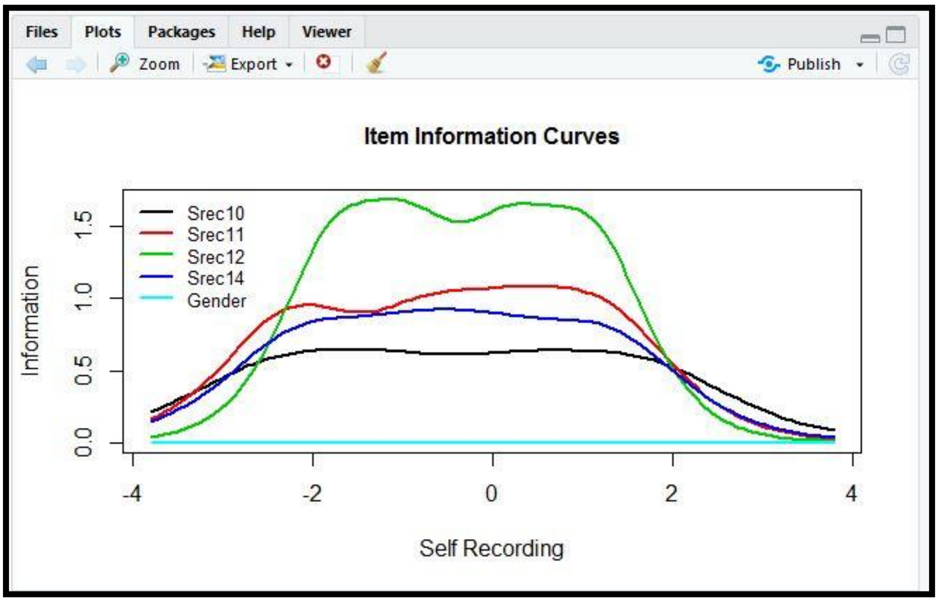


Figure 4.106 **Item Information Curves (IIC) – Self Recording**

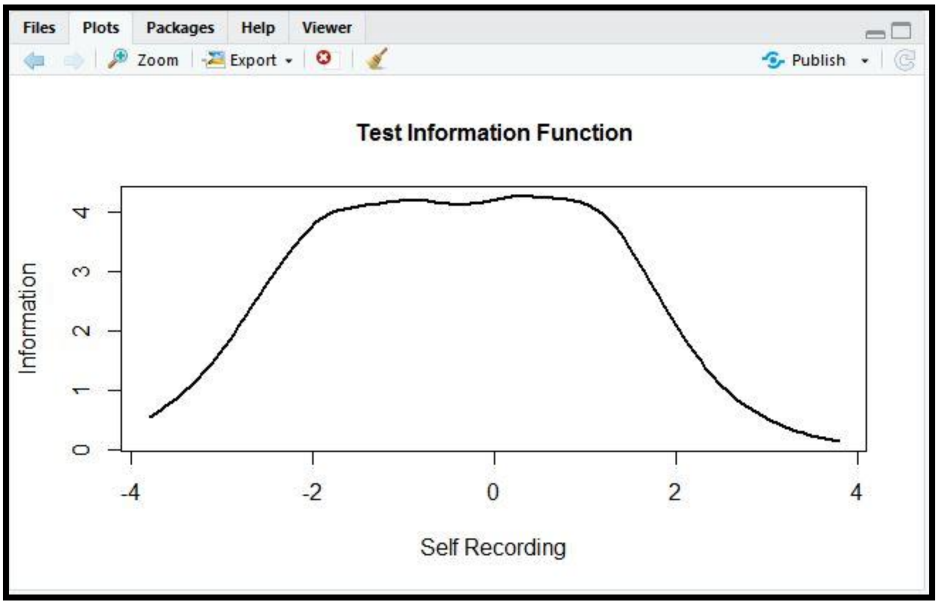
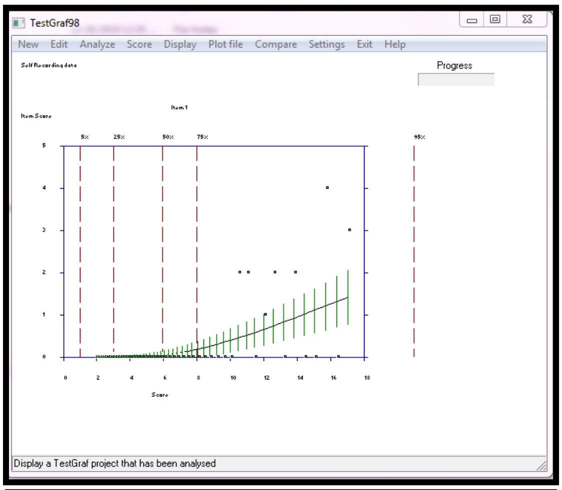
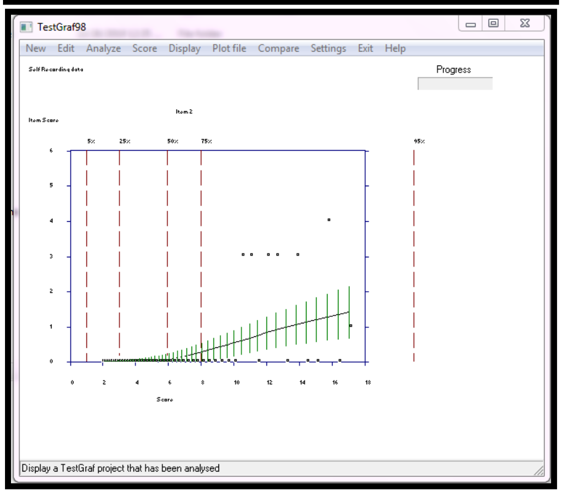


Figure 4.107 **Test Information Curve (TIC) – Self Recording**





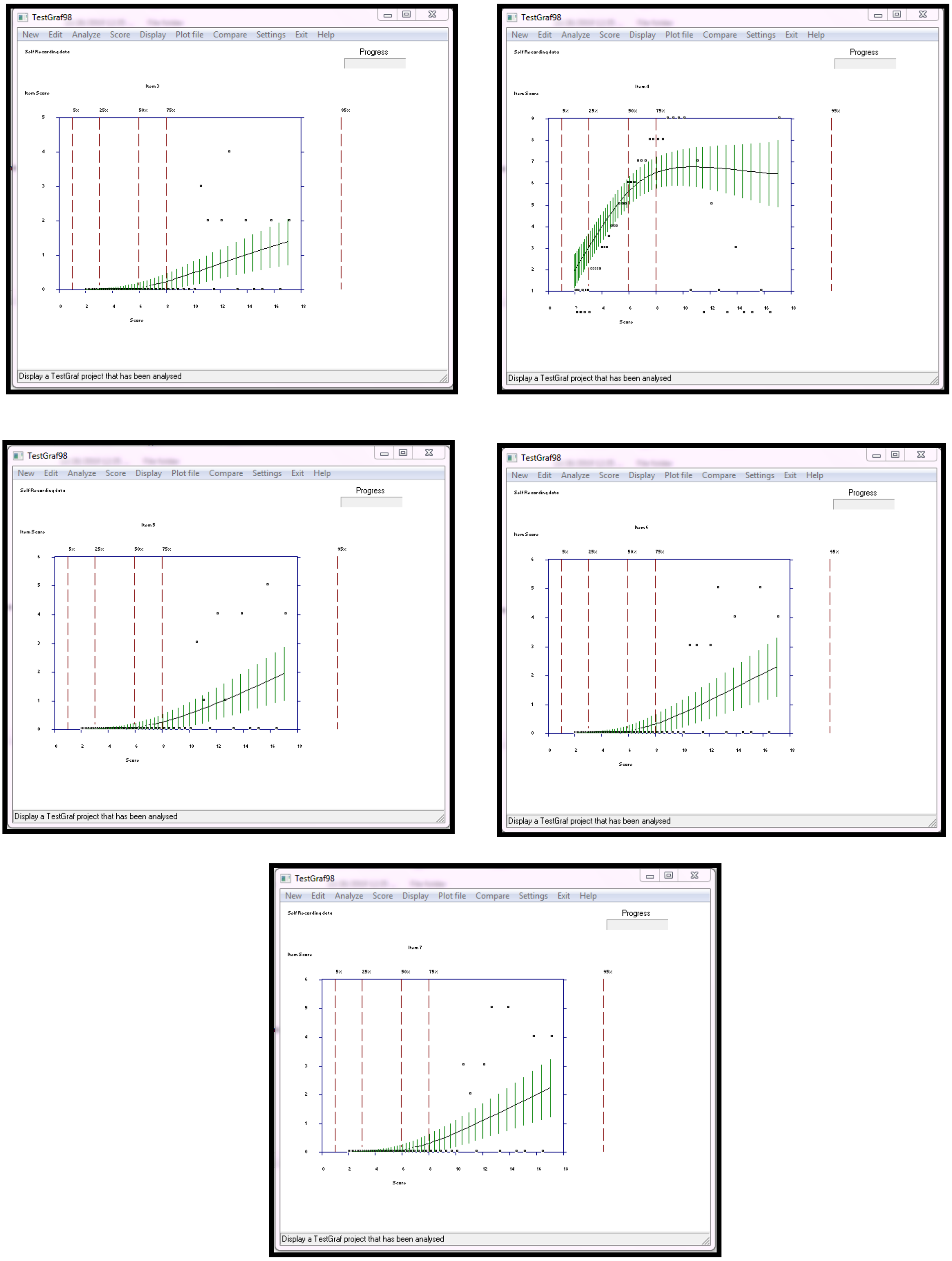
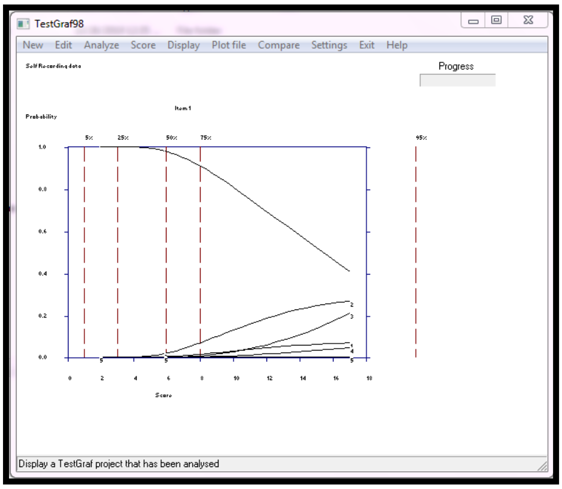
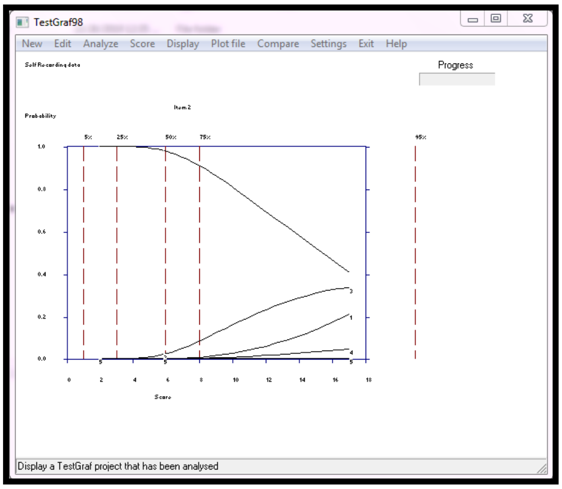
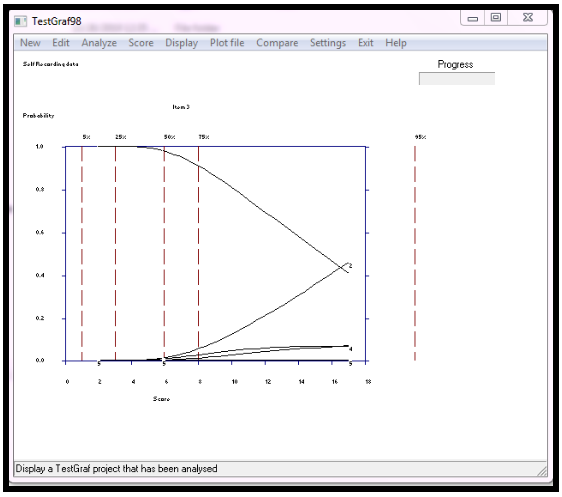
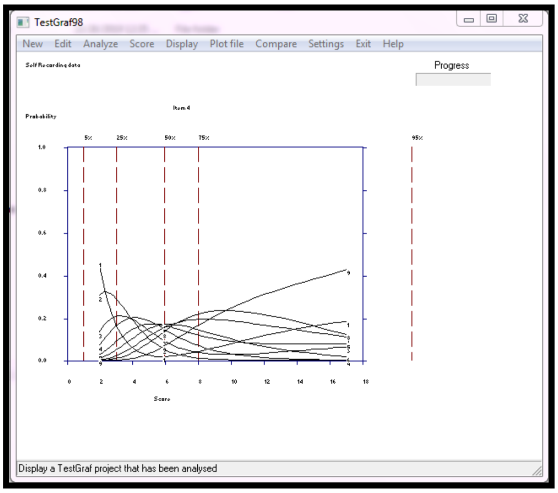


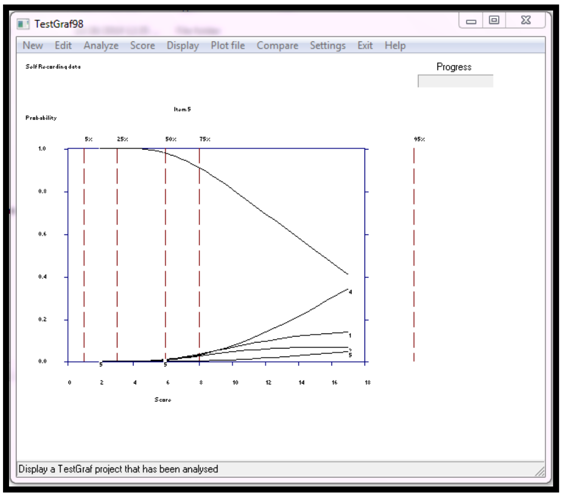
Figure 4.108 **Non-Parametric Item Characteristic Curves (ICC) of Self Recoding Items using TestGraf98**


TestGraf98
New Edit Analyze Score Display Plot file Compare Settings Exit Help
Progress
Display a TestGraf project that has been analysed


TestGraf98
New Edit Analyze Score Display Plot file Compare Settings Exit Help
Progress
Display a TestGraf project that has been analysed


TestGraf98
New Edit Analyze Score Display Plot file Compare Settings Exit Help
Progress
Display a TestGraf project that has been analysed


TestGraf98
New Edit Analyze Score Display Plot file Compare Settings Exit Help
Progress
Display a TestGraf project that has been analysed


TestGraf98
New Edit Analyze Score Display Plot file Compare Settings Exit Help
Progress
Display a TestGraf project that has been analysed

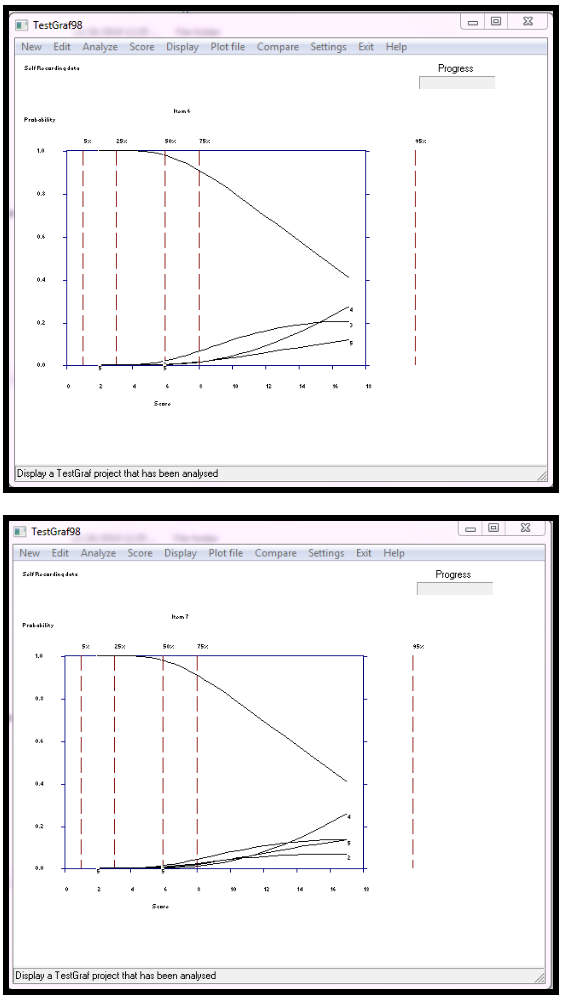


Figure 4.109 **Non-Parametric Option Characteristic Curves (OCC) of Self Recoding Items using TestGraf98**

5. Items and Options Performance of Scale Five - Self Evaluation:

```
Coefficients:
$Sevel15
Extrmt1  Extrmt2  Extrmt3  Extrmt4   Dscrmn
 -2.048   -0.955   -0.086   0.796    1.492

$Sevel16
Extrmt1  Extrmt2  Extrmt3  Extrmt4   Dscrmn
 -1.837   -0.654    0.319   1.163    1.911

$Sevel17
Extrmt1  Extrmt2  Extrmt3  Extrmt4   Dscrmn
 -1.770   -0.590    0.439   1.302    1.780

$Sevel18
Extrmt1  Extrmt2  Extrmt3  Extrmt4   Dscrmn
 -1.539   -0.722    0.287   1.198    3.313

$Sevel19
Extrmt1  Extrmt2  Extrmt3  Extrmt4   Dscrmn
 -2.151   -0.871    0.365   1.999    1.330

$Sevel20
Extrmt1  Extrmt2  Extrmt3  Extrmt4   Dscrmn
 -2.049   -0.868    0.099   1.246    1.953

$Gender
Extrmt1   Dscrmn
  2.112  -14.739
```

Figure 4.110 **Item Discrimination Report – Self Evaluation – Original Scale**

```
Call:
grm(data = Self_Evaluation_Data_Copy, constrained = FALSE)

Coefficients:
$Sevel15
Extrmt1  Extrmt2  Extrmt3  Extrmt4   Dscrmn
 -1.981   -0.937   -0.095   0.756    1.602

$Sevel16
Extrmt1  Extrmt2  Extrmt3  Extrmt4   Dscrmn
 -1.817   -0.684    0.267   1.121    1.956

$Sevel18
Extrmt1  Extrmt2  Extrmt3  Extrmt4   Dscrmn
 -1.570   -0.765    0.270   1.207    3.059

$Sevel20
Extrmt1  Extrmt2  Extrmt3  Extrmt4   Dscrmn
 -2.064   -0.898    0.076   1.220    1.978

$Gender
Extrmt1   Dscrmn
  2.171   -7.592


Log.Lik: -578.077
```

Figure 4.111**Item Discrimination Report – Self Evaluation – Parsimonious Scale**

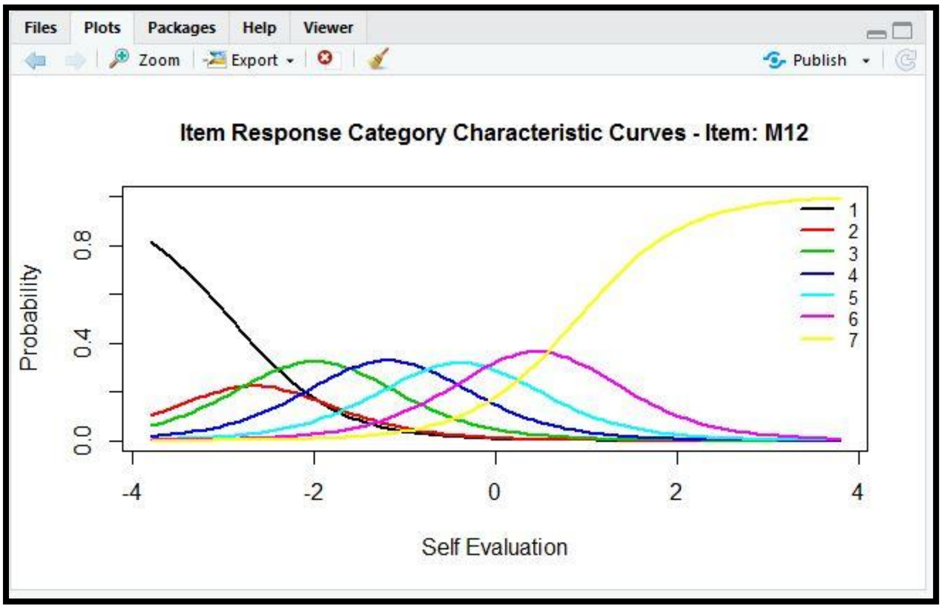


Figure 4.112 **Item Characteristic Curves (ICC) – M12**

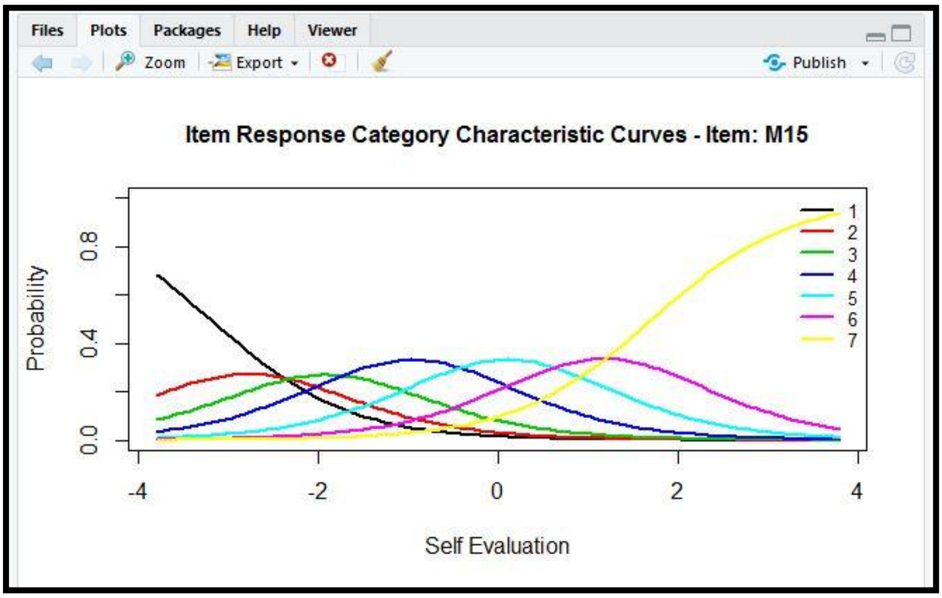


Figure 4.113 **Item Characteristic Curve (ICC) – M15**

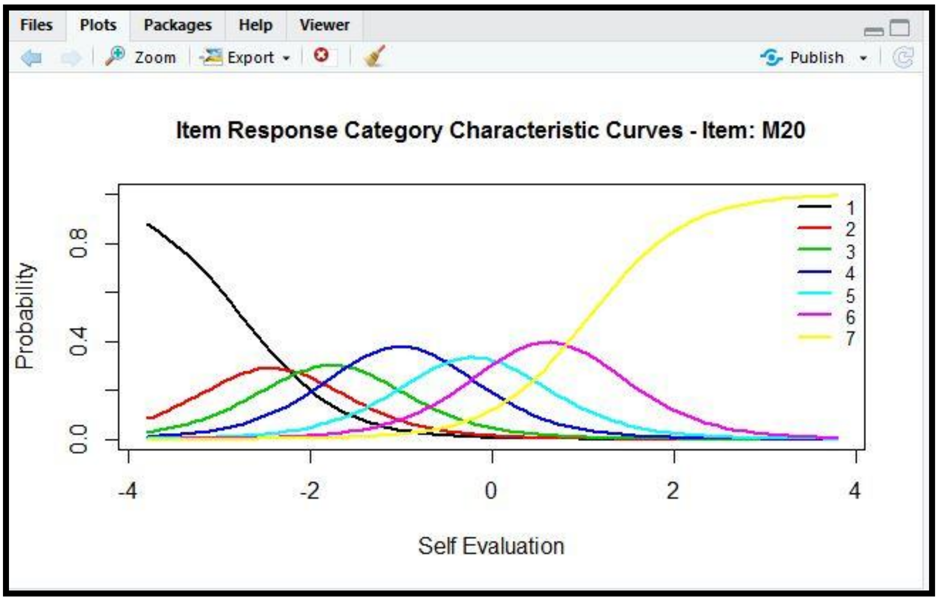


Figure 4.114 **Item Characteristic Curves (ICC) – M20**

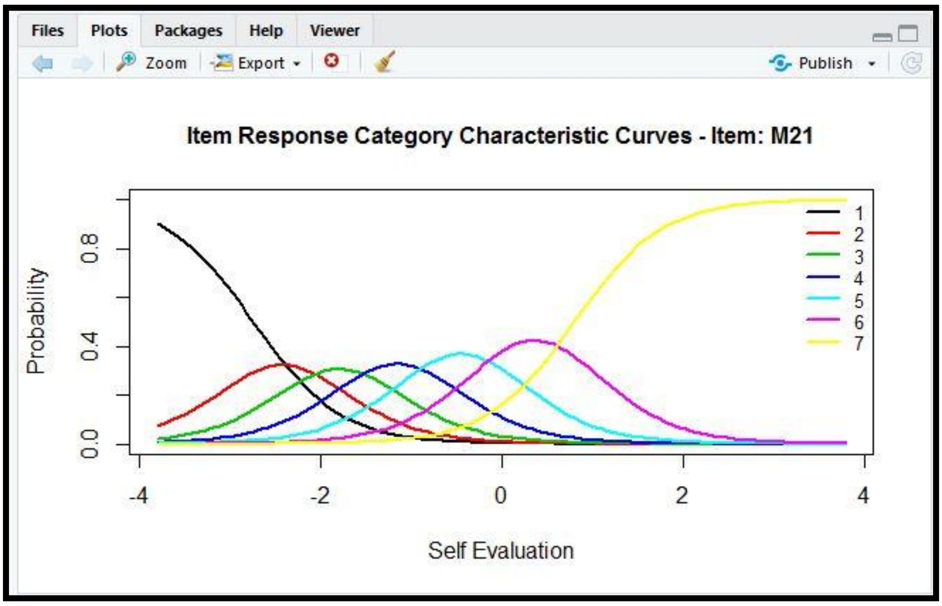


Figure 4.115 **Item Characteristic Curves (ICC) – M21**

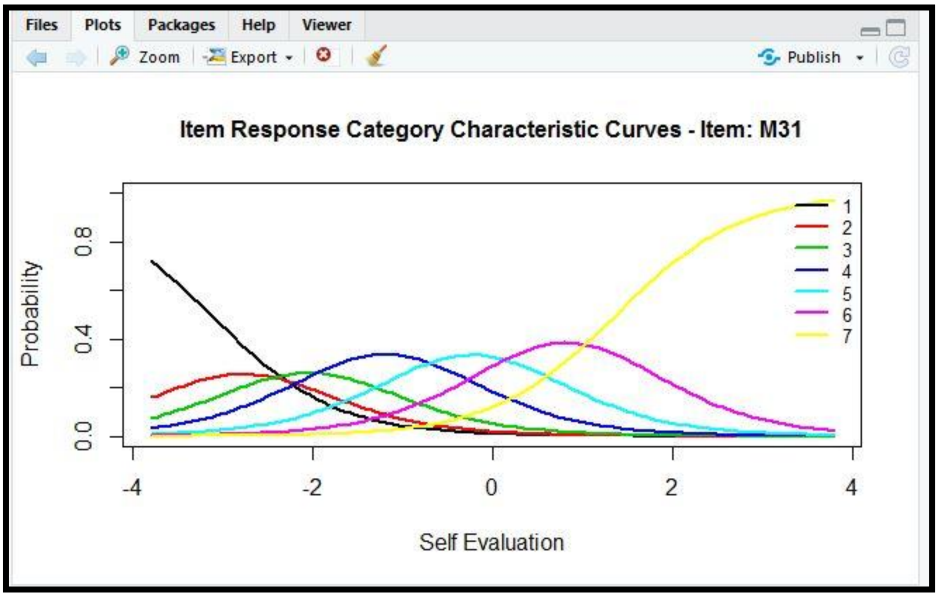


Figure 4.116 **Item Characteristic Curve (ICC) – M31**

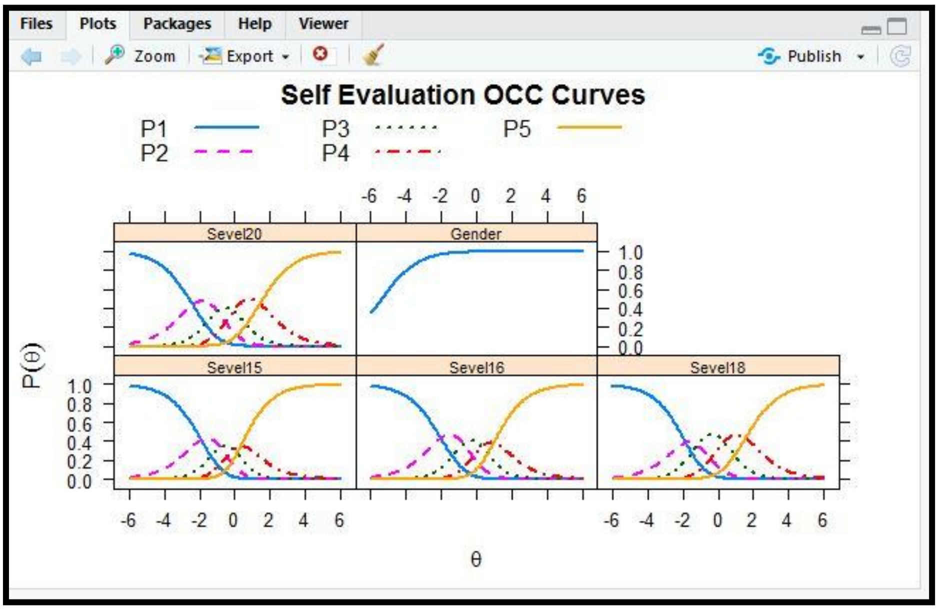


Figure 4.117 **Option Characteristic Curves (OCC) – Self Evaluation**

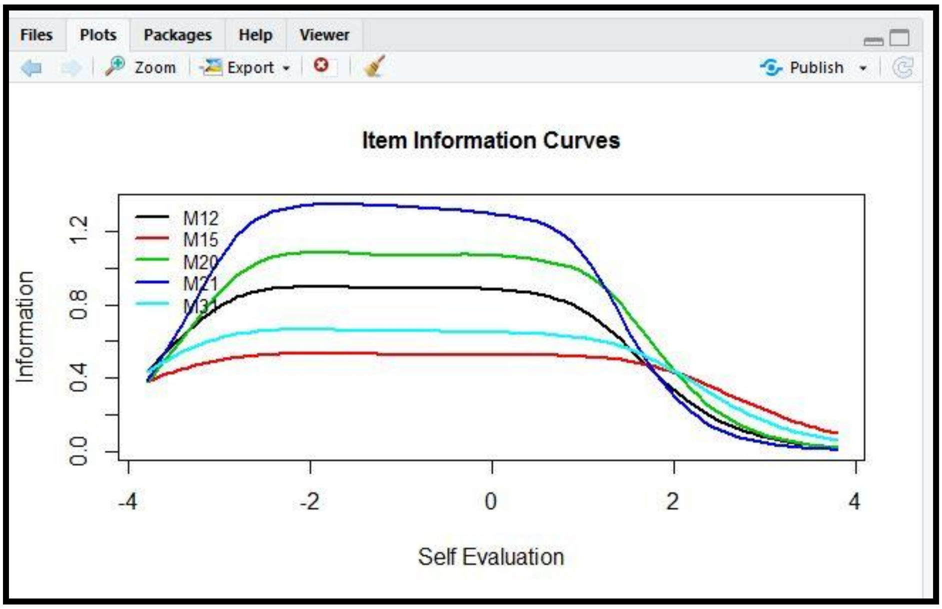


Figure 4.118 **Item Information Curve (IIC) – Self Evaluation**

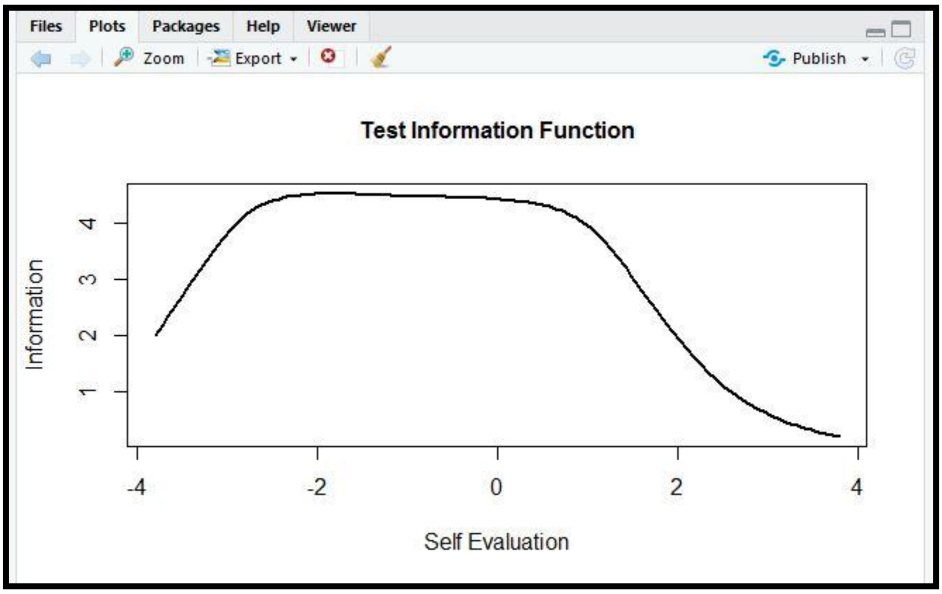
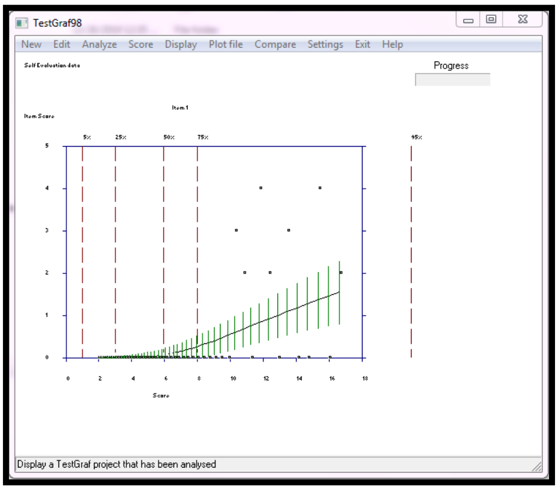
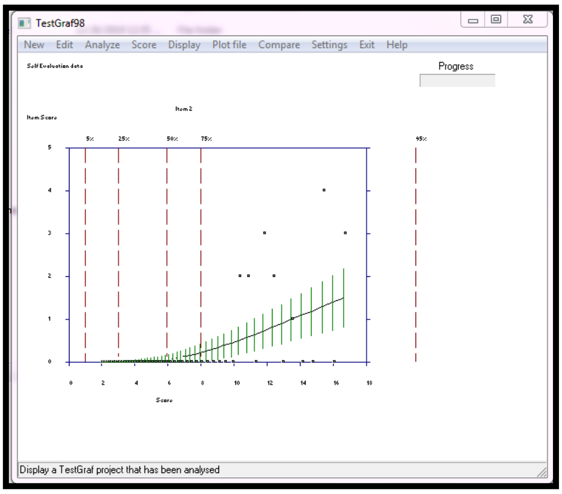
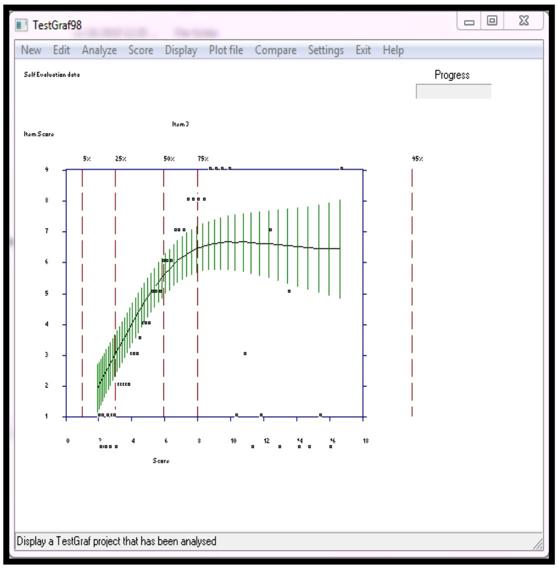
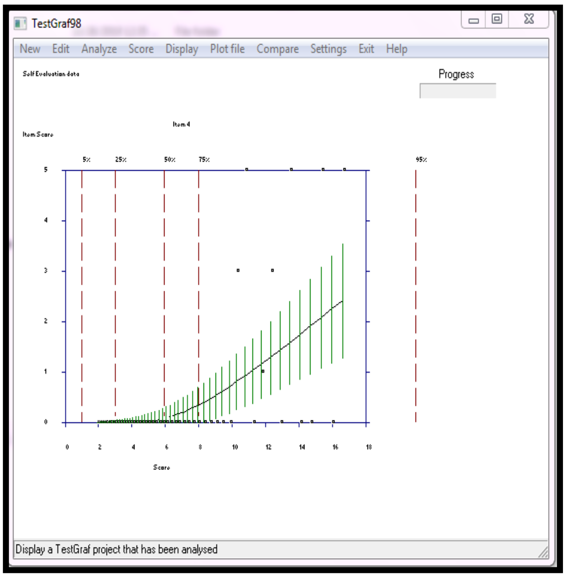
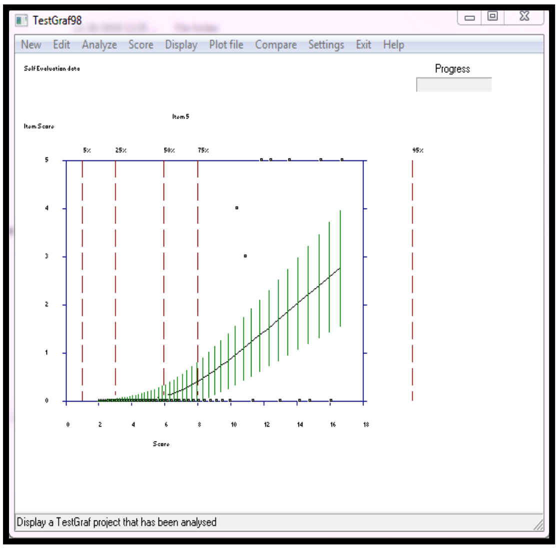


Figure 4.119 **Test Information Curve (TIC) – Self Evaluation**


TestGraf98
New Edit Analyze Score Display Plot file Compare Settings Exit Help
Progress
Display a TestGraf project that has been analysed

TestGraf98
New Edit Analyze Score Display Plot file Compare Settings Exit Help
Progress
Display a TestGraf project that has been analysed

TestGraf98
New Edit Analyze Score Display Plot file Compare Settings Exit Help
Progress
Display a TestGraf project that has been analysed

TestGraf98
New Edit Analyze Score Display Plot file Compare Settings Exit Help
Progress
Display a TestGraf project that has been analysed

TestGraf98
New Edit Analyze Score Display Plot file Compare Settings Exit Help
Progress
Display a TestGraf project that has been analysed

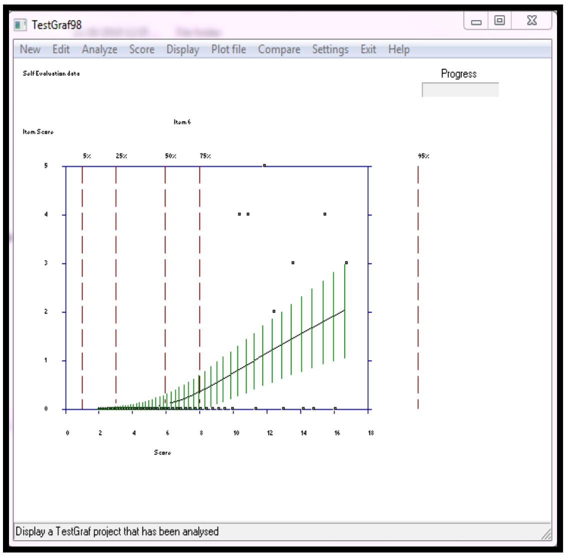
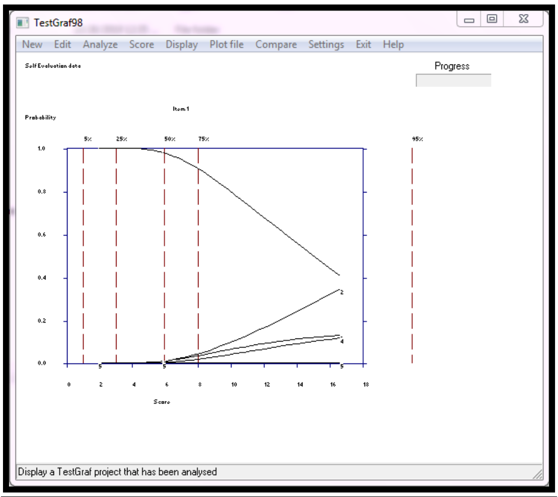
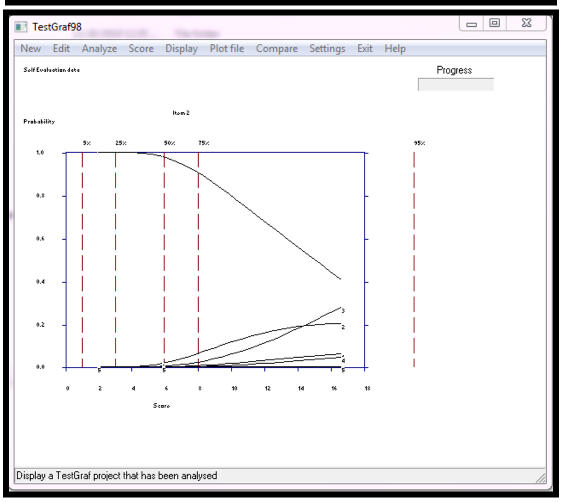


Figure 4.120 **Non-Parametric Item Characteristic Curves of Self Evaluation Items using TestGraf98:**





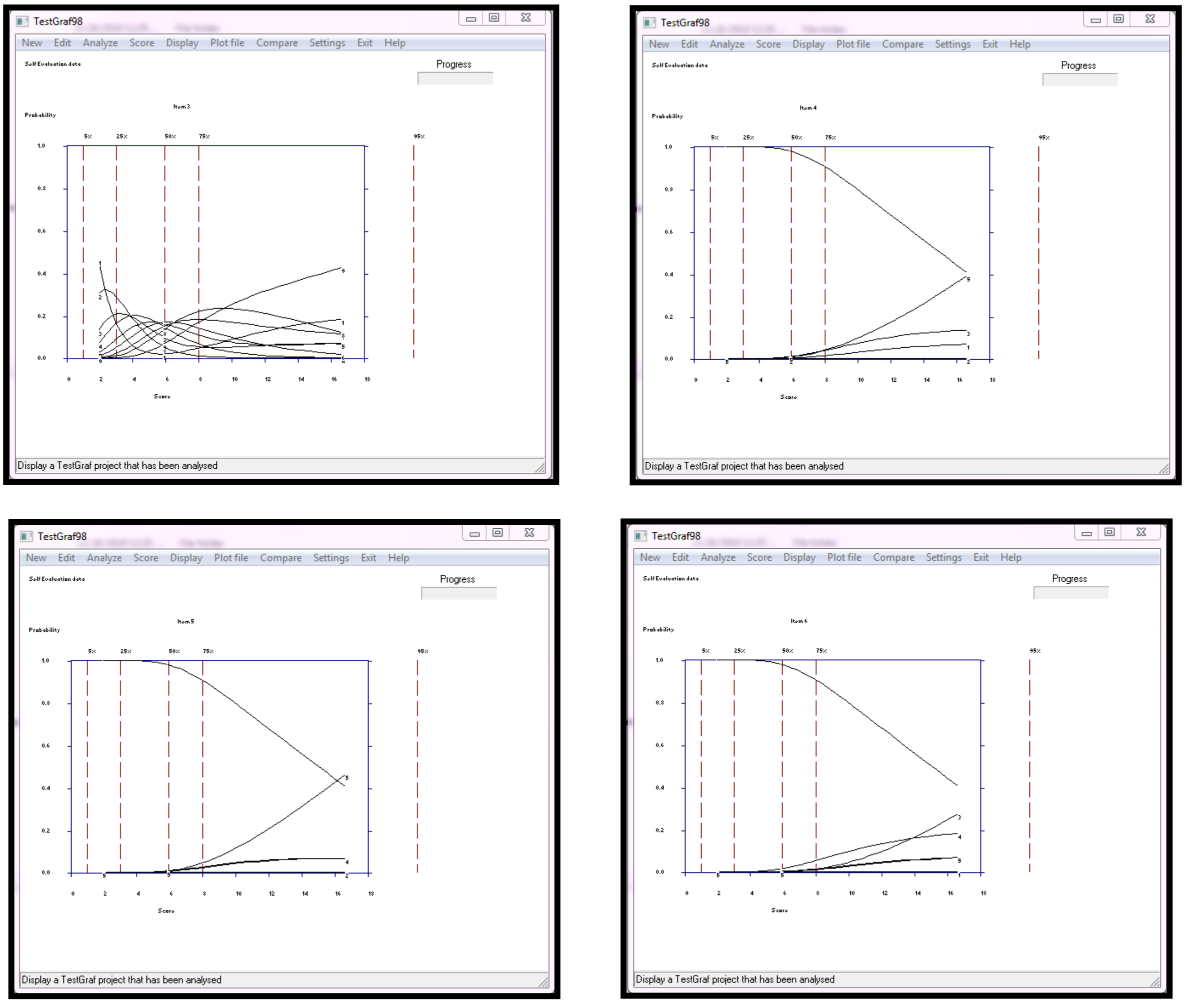


Figure 4.121 **Non Parametric Option Characteristic Curves (OCC) Self Evaluation Items using TestGraf98:**

6. Items and Options Performance of Scale Six – Academic Intrinsic Motivation:

```
Coefficients:
        Extrmt1  Extrmt2  Extrmt3  Extrmt4  Extrmt5  Extrmt6  Dscrmn
IMa2     -3.607   -2.554   -1.565   -0.366    0.637    1.626   0.891
IMa9     -2.861   -2.051   -1.209   -0.284    0.595    1.968   1.144
IMa16    -2.532   -1.922   -1.363   -0.348    0.513    1.710   1.412
IMa23    -3.482   -2.225   -1.358   -0.378    0.553    1.851   1.159
IMk3     -2.548   -1.846   -1.152   -0.245    0.637    1.693   1.303
IMk10    -2.207   -1.575   -1.039   -0.163    0.499    1.431   1.495
IMk17    -2.725   -1.718   -0.964   -0.195    0.406    1.570   1.672
IMK24    -2.781   -2.114   -1.101   -0.180    0.890    2.004   1.181
IMse1    -2.029   -1.027   -0.477    0.465    1.172    1.931   0.927
IMse8    -2.255   -1.566   -0.941   -0.331    0.477    1.160   1.484
IMse15   -1.749   -1.137   -0.696   -0.126    0.344    0.876   2.202
IMse22   -2.756   -1.995   -1.124   -0.178    0.833    1.840   1.138

Log.Lik: -5851.408

> fit2 <- grm(AIM_Data_Copy, constrained = FALSE)
> fit2

Call:
grm(data = AIM_Data_Copy, constrained = FALSE)

Coefficients:
        Extrmt1  Extrmt2  Extrmt3  Extrmt4  Extrmt5  Extrmt6  Dscrmn
IMa9     -3.070   -2.199   -1.294   -0.300    0.636    2.110   1.034
IMa16    -2.627   -1.988   -1.409   -0.359    0.536    1.783   1.322
IMk10    -2.165   -1.532   -1.008   -0.146    0.505    1.414   1.538
IMk17    -2.887   -1.813   -1.011   -0.200    0.430    1.653   1.504
IMK24    -2.606   -1.986   -1.041   -0.172    0.835    1.889   1.295
IMse8    -2.160   -1.491   -0.888   -0.308    0.458    1.109   1.611
IMse15   -1.722   -1.123   -0.694   -0.133    0.327    0.849   2.314
IMse22   -2.470   -1.792   -1.015   -0.163    0.746    1.652   1.337

Log.Lik: -3883.177
```

Figure 4.122 **Item Discrimination Report – Academic Intrinsic Motivation**

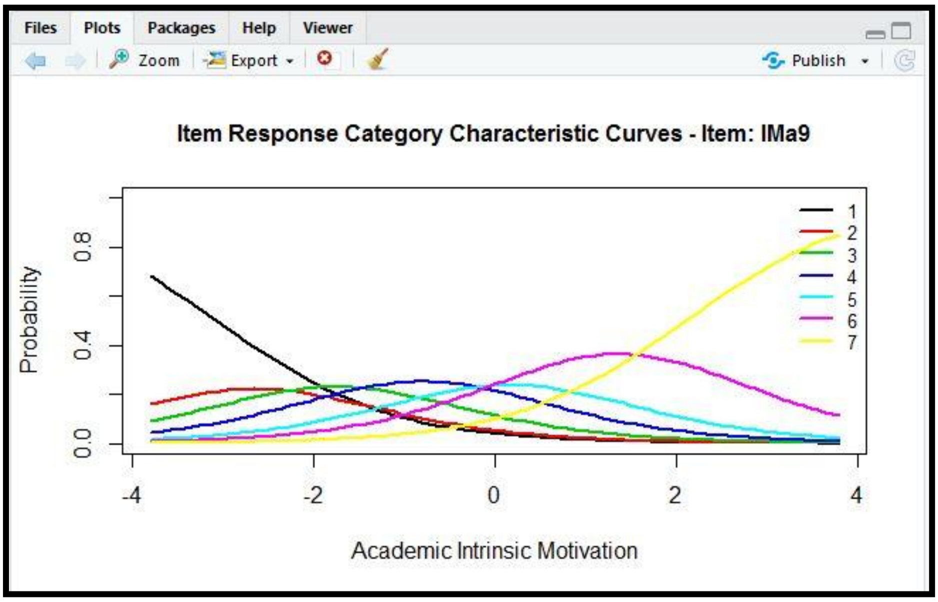


Figure 4.123**Item Characteristic Curves (ICC) – Ima9**

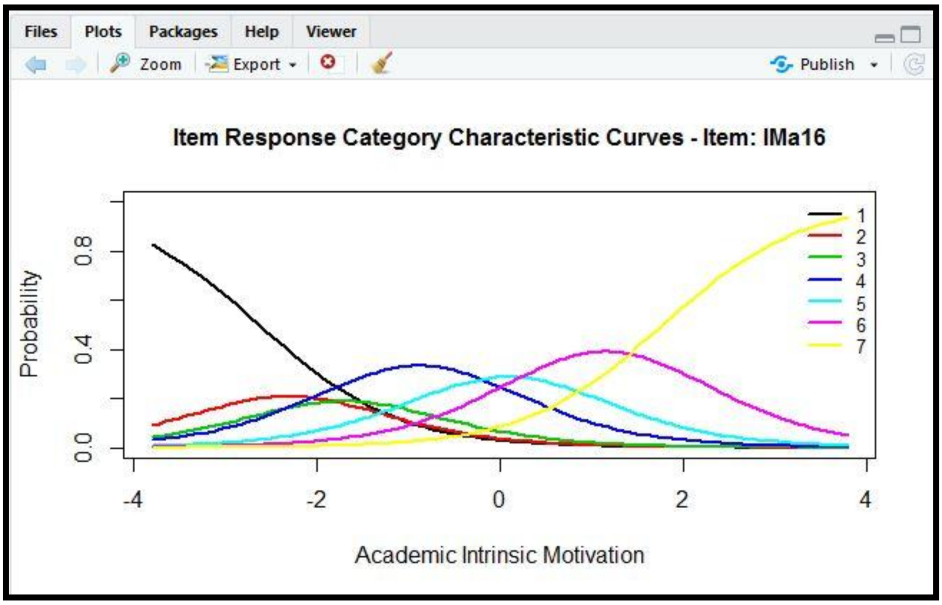


***Figure 4.124* Item Characteristic Curves (ICC) – Ima16**

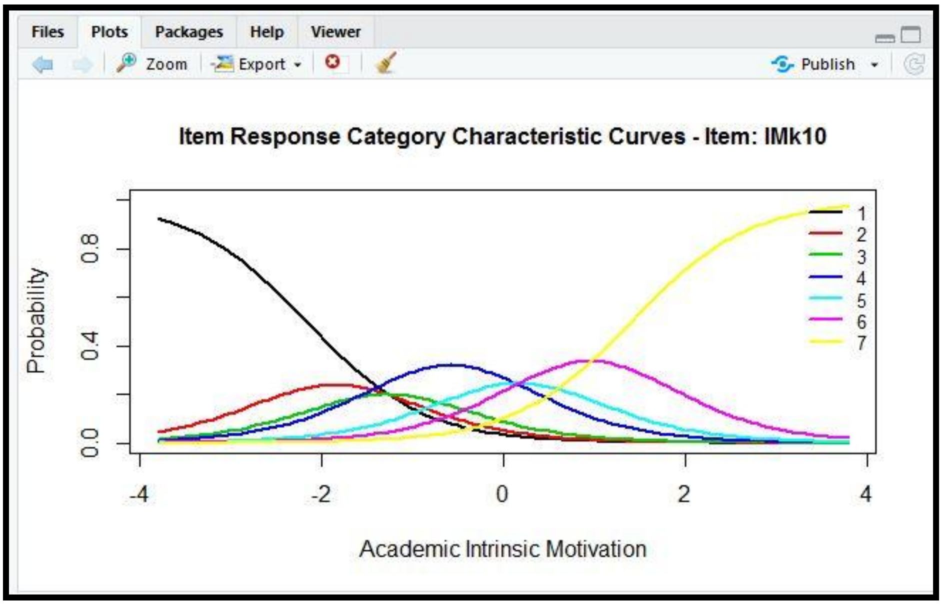


Figure 4.125 **Item Characteristic Curves (ICC) – Imk10**

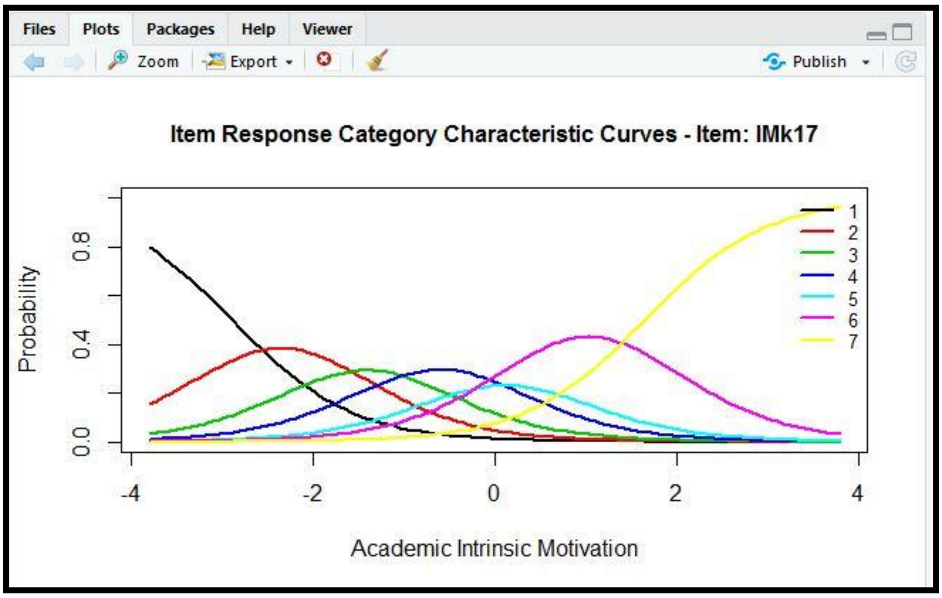


Figure 4.126 **Item Characteristic Curves (ICC) – Imk17**

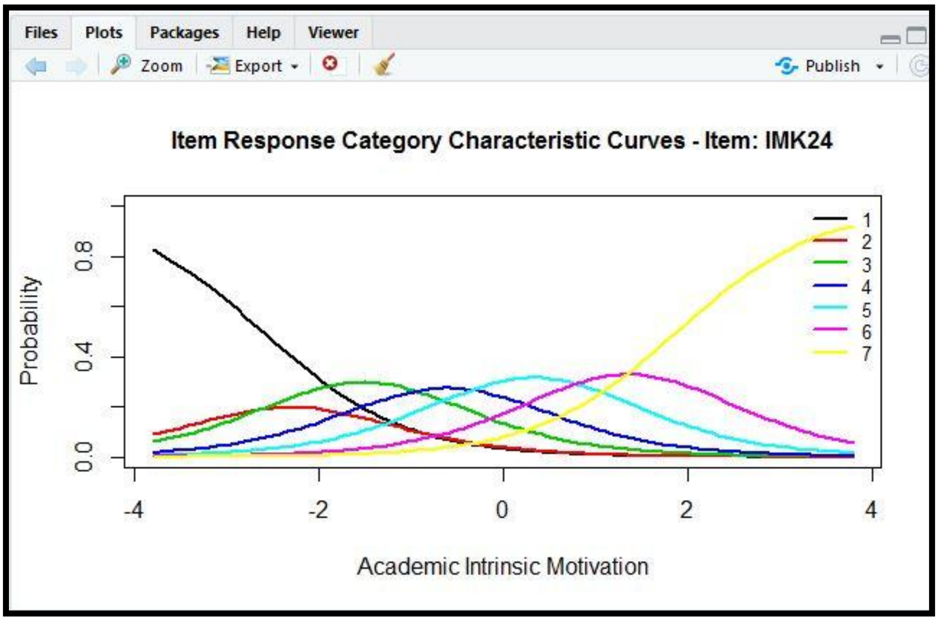


Figure 4.127 **Item Characteristic Curves (ICC) – Imk24**

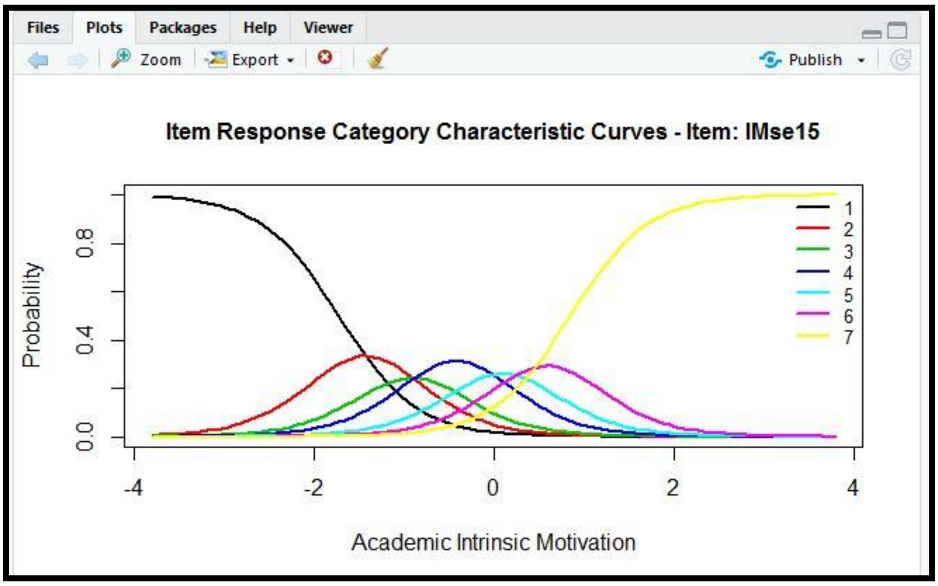


Figure 4.128 **Item Characteristic Curves (ICC) – Imse15**

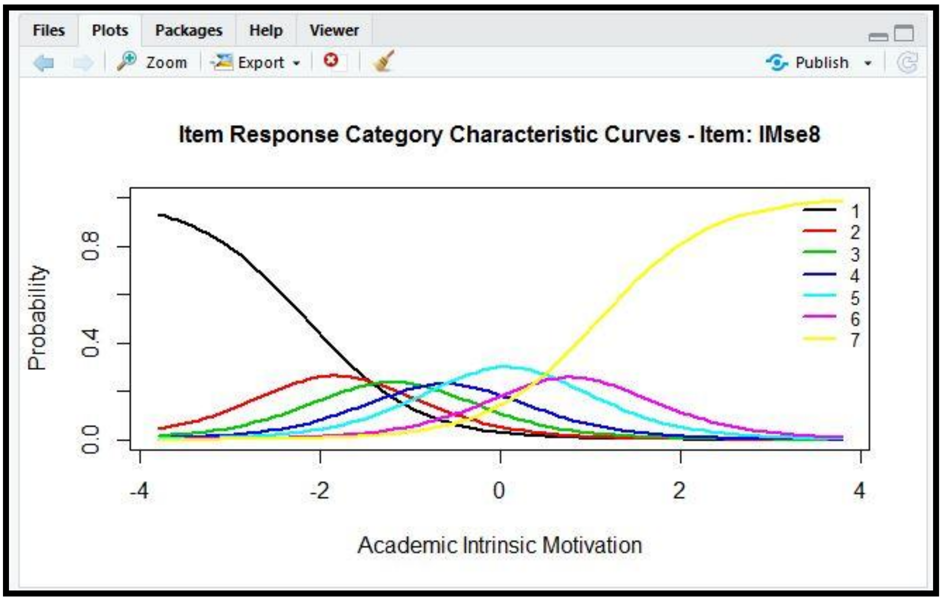


Figure 4.129 **Item Characteristic Curves (ICC) – Imse8**

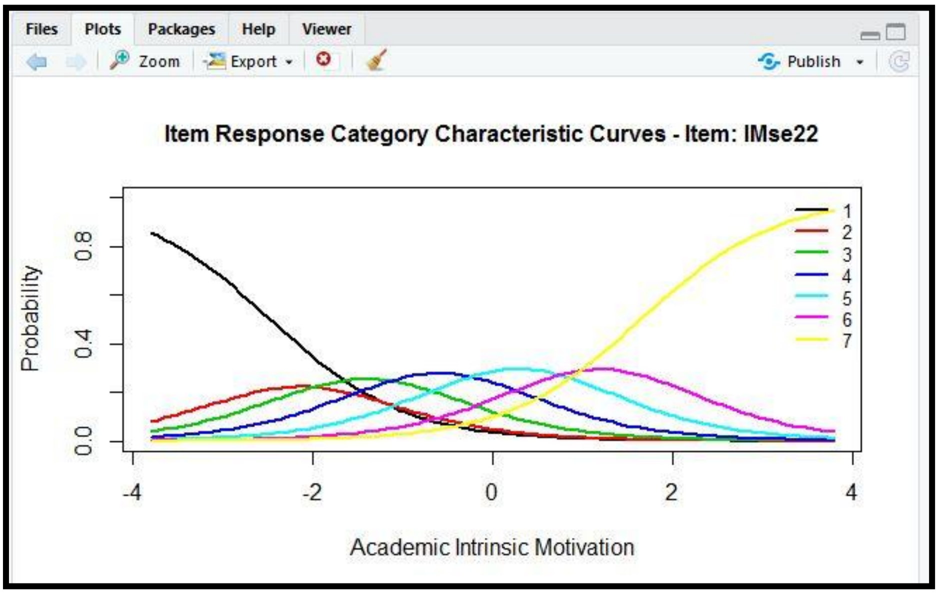


Figure 4.130 **Item Characteristic Curves (ICC) – Imse22**

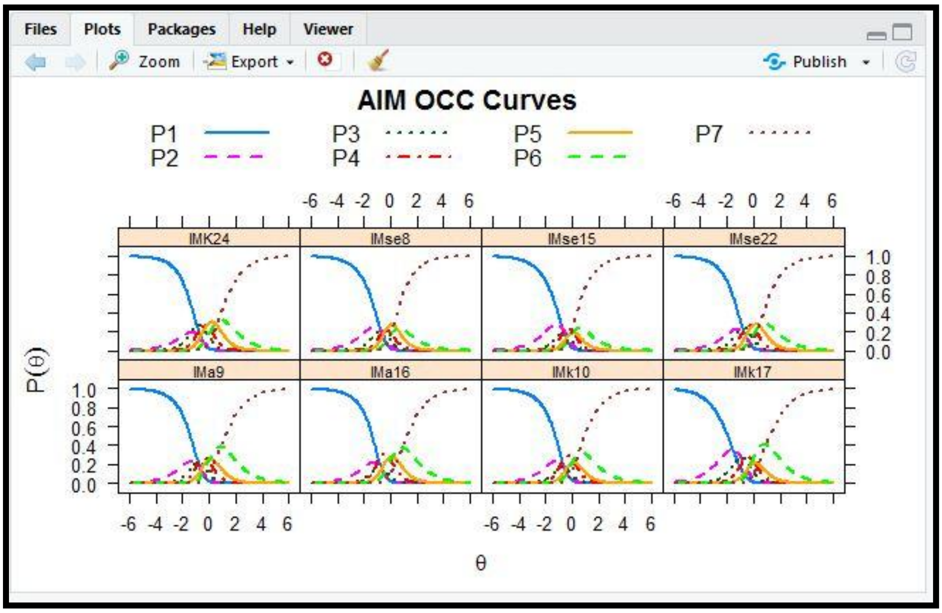


Figure 4.131 **Option Characteristic Curves (OCC) – Academic Intrinsic Motivation**

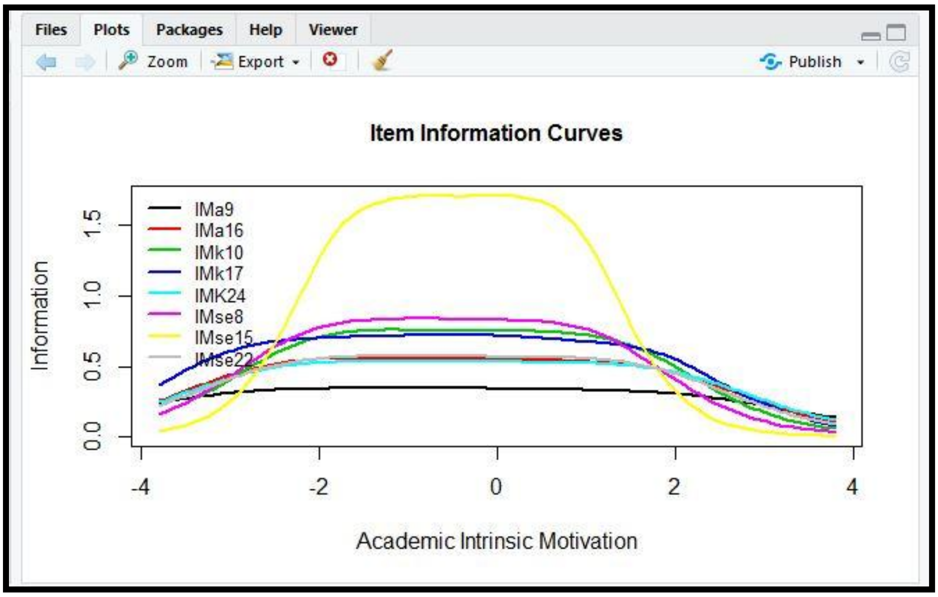


Figure 4.132 **Item Information Curves (IIC) – Academic Intrinsic Motivation**

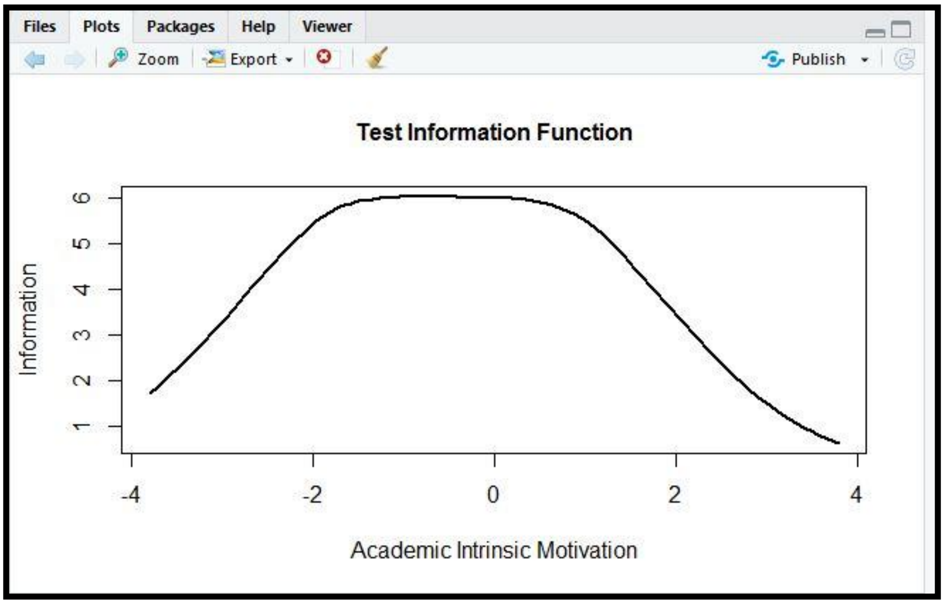
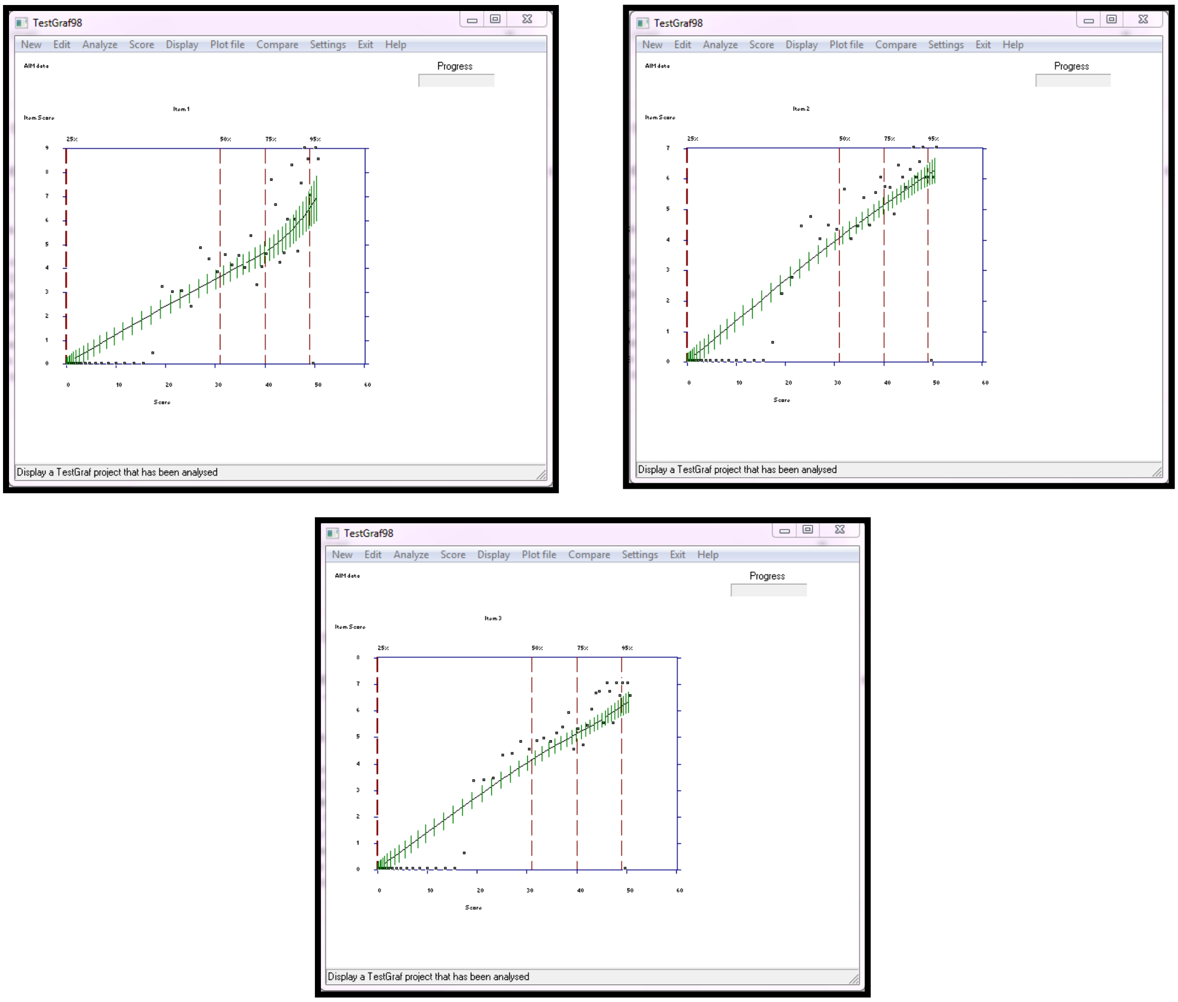


Figure 4.133 **Test Information Curves (TIC) – Academic Intrinsic Motivation**



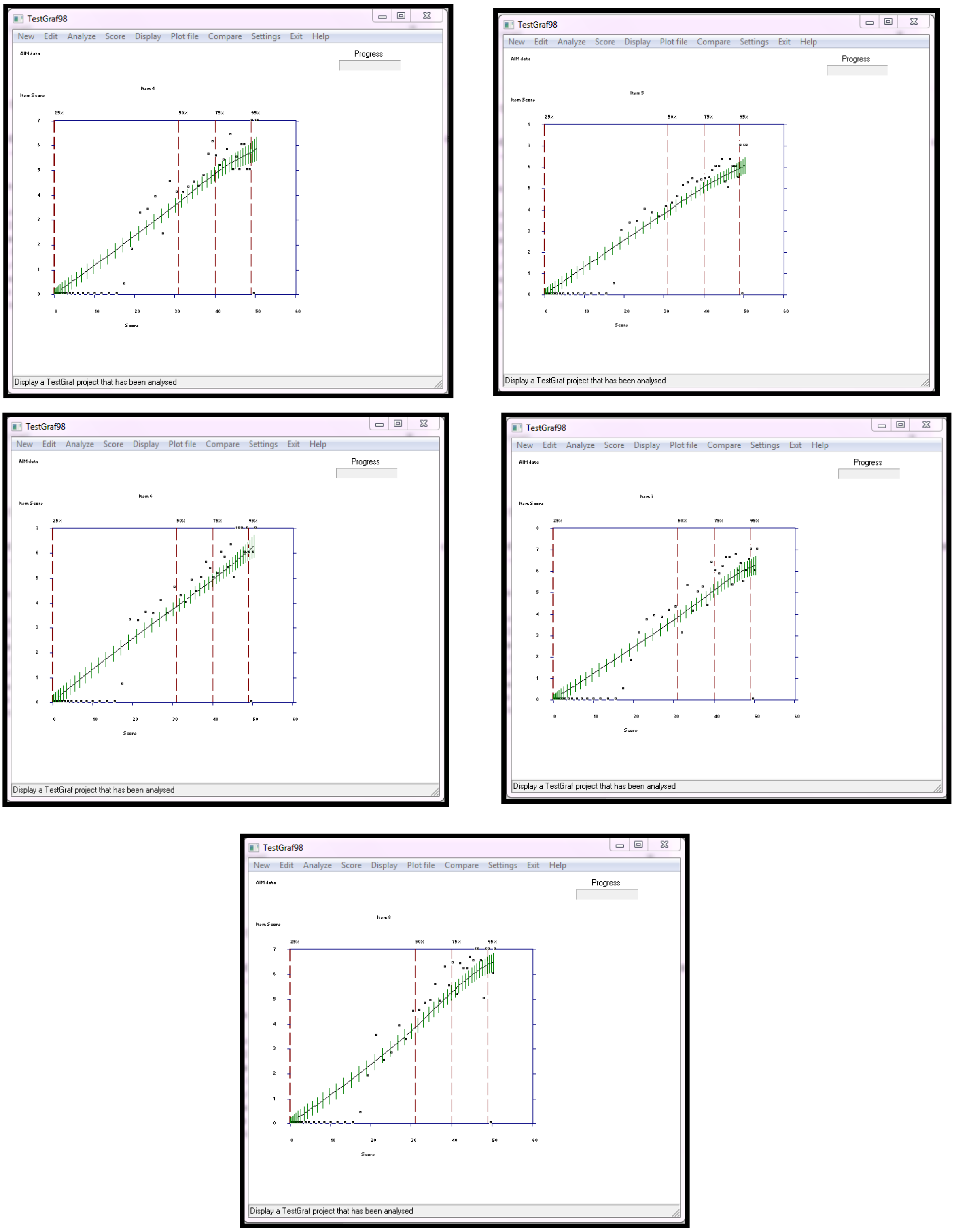
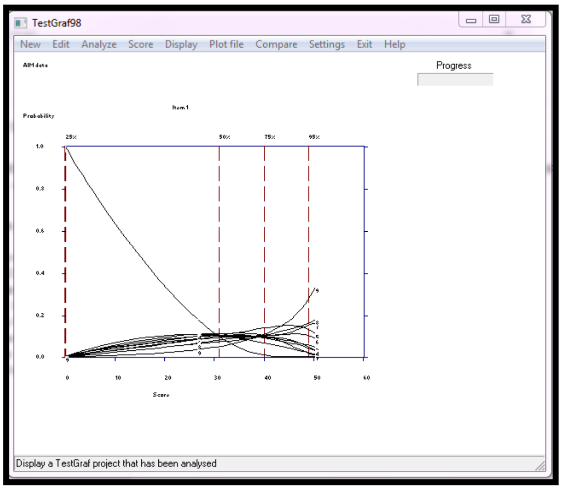
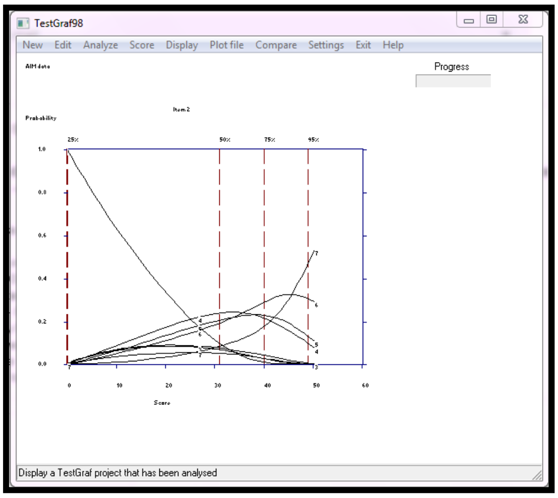
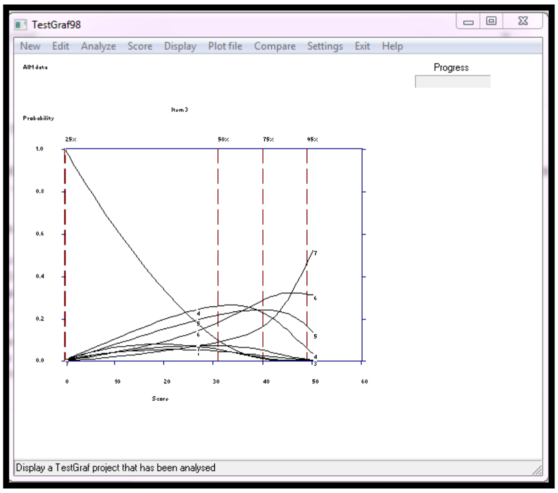
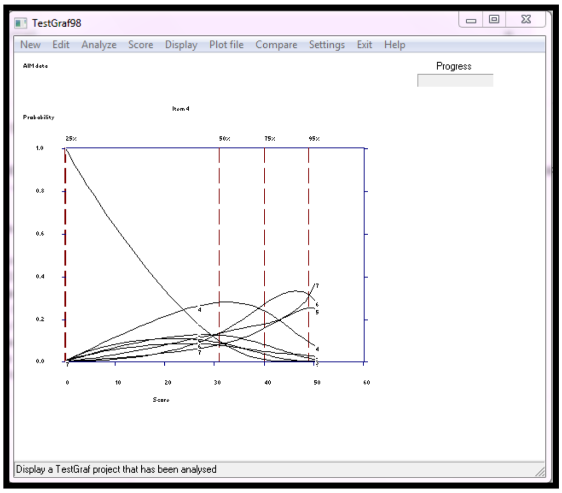


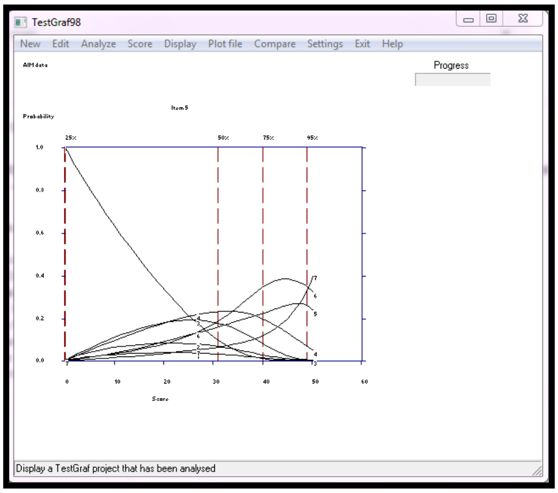
Figure 4.134 **Non Parametric Item Characteristic Curves (ICC) of Academic Intrinsic Motivation Items using TestGraf98:**


TestGraf98
New Edit Analyze Score Display Plot file Compare Settings Exit Help
Progress
Display a TestGraf project that has been analysed


TestGraf98
New Edit Analyze Score Display Plot file Compare Settings Exit Help
Progress
Display a TestGraf project that has been analysed


TestGraf98
New Edit Analyze Score Display Plot file Compare Settings Exit Help
Progress
Display a TestGraf project that has been analysed


TestGraf98
New Edit Analyze Score Display Plot file Compare Settings Exit Help
Progress
Display a TestGraf project that has been analysed


TestGraf98
New Edit Analyze Score Display Plot file Compare Settings Exit Help
Progress
Display a TestGraf project that has been analysed

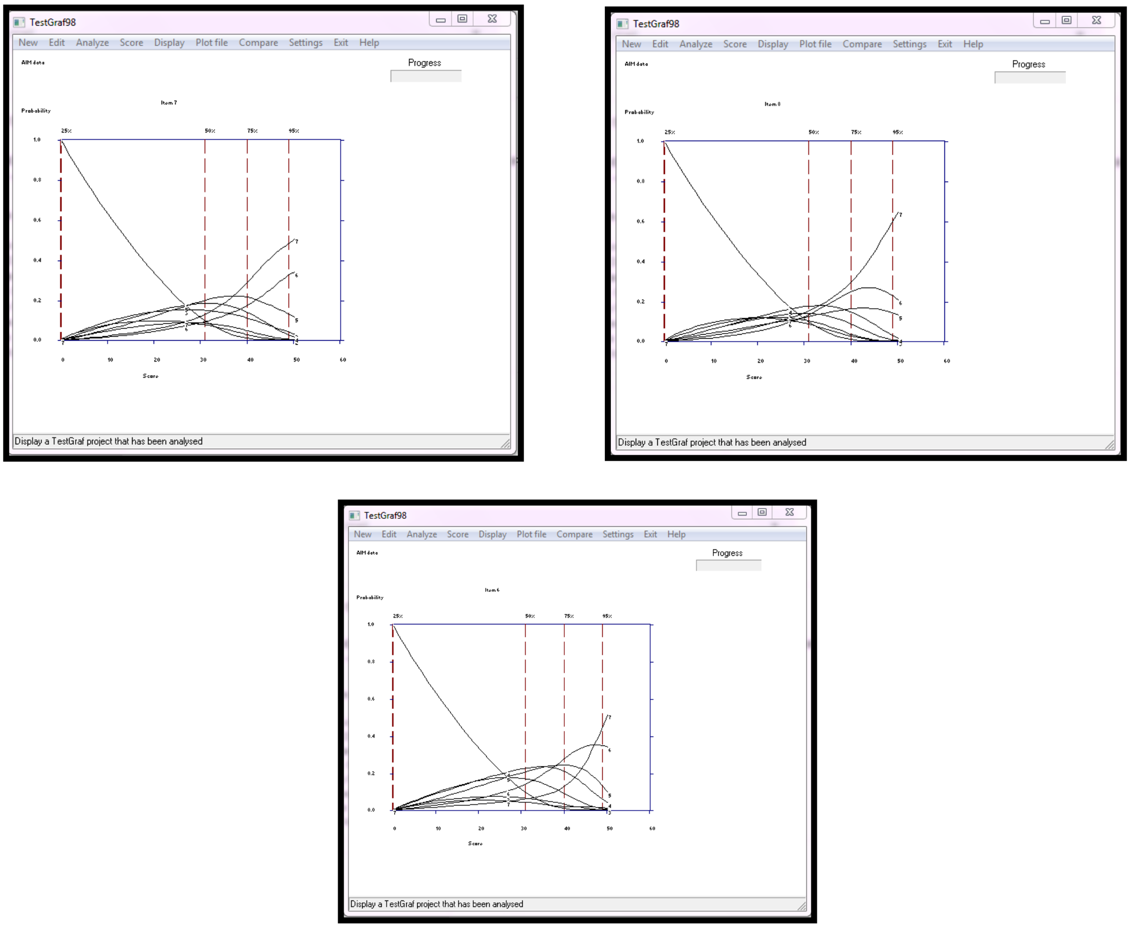


Figure 4.135 **Non Parametric Option Characteristic Curves (OCC) Academic Intrinsic Motivation Items using TestGraf98:**

7. Items and Options Performance of Scale Seven – Self Efficacy:

```
Call:
grm(data = Self_Efficacy, constrained = FALSE)

Coefficients:
     Extrmt1  Extrmt2  Extrmt3  Extrmt4  Extrmt5  Extrmt6  Dscrmn
M5    -3.030   -2.308   -1.533   -0.667    0.211    1.288   1.362
M6    -3.088   -2.293   -1.365   -0.353    0.755    1.951   1.214
M12   -2.953   -2.406   -1.597   -0.780    0.006    0.909   1.660
M15   -3.037   -2.227   -1.419   -0.403    0.615    1.643   1.402
M20   -2.758   -2.111   -1.435   -0.571    0.174    1.068   1.843
M21   -2.896   -2.200   -1.546   -0.851   -0.073    0.834   1.854
M29   -3.000   -2.294   -1.495   -0.448    0.582    1.696   1.372
M31   -2.987   -2.313   -1.611   -0.678    0.247    1.328   1.548

Log.Lik: -23278.82

> library(haven)
> Self_Efficacy_Copy <- read_sav("D:/Item Discrimination of Final Tool Items in R/MLSQ/
Self Efficacy - Copy.sav")
> View(Self_Efficacy_Copy)
> fit1 <- grm(Self_Efficacy_Copy, constrained = FALSE)
> fit1

Call:
grm(data = Self_Efficacy_Copy, constrained = FALSE)

Coefficients:
     Extrmt1  Extrmt2  Extrmt3  Extrmt4  Extrmt5  Extrmt6  Dscrmn
M12   -2.921   -2.381   -1.585   -0.778    0.003    0.907   1.685
M15   -3.202   -2.337   -1.486   -0.421    0.643    1.720   1.295
M20   -2.744   -2.100   -1.430   -0.575    0.170    1.072   1.856
M21   -2.738   -2.089   -1.477   -0.820   -0.074    0.803   2.066
M31   -3.133   -2.412   -1.673   -0.702    0.257    1.378   1.445

Log.Lik: -14481.65
```

Figure 4.136 **Item Discrimination Report – Self Efficacy**

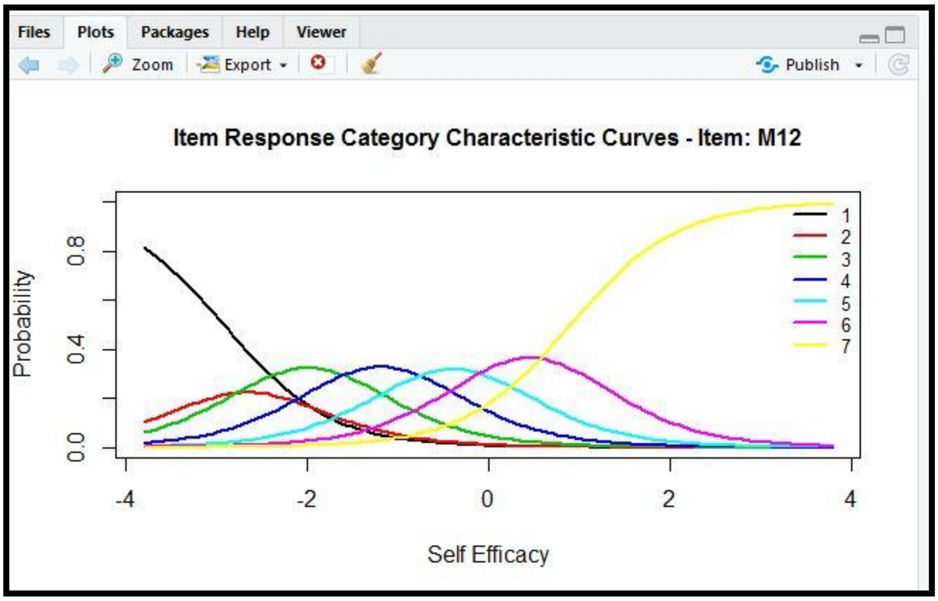


Figure 4.137 **Item Characteristic Curve (ICC)– M12**

Figure 4.138 **Item Characteristic Curve (ICC)–M16**

Figure 4.139 **Item Characteristic Curve (ICC)– M20**

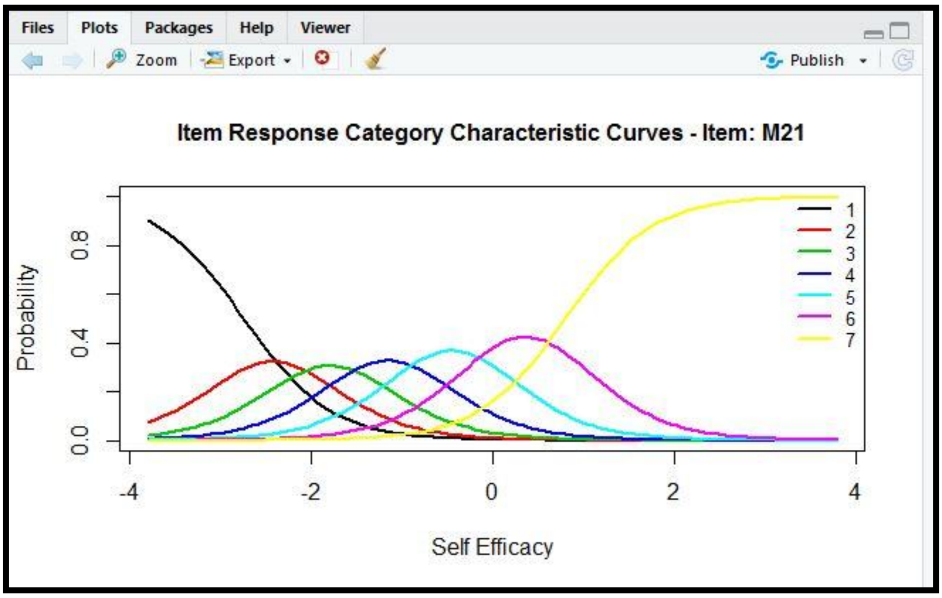


Figure 4.140 **Item Characteristic Curve (ICC)– M21**

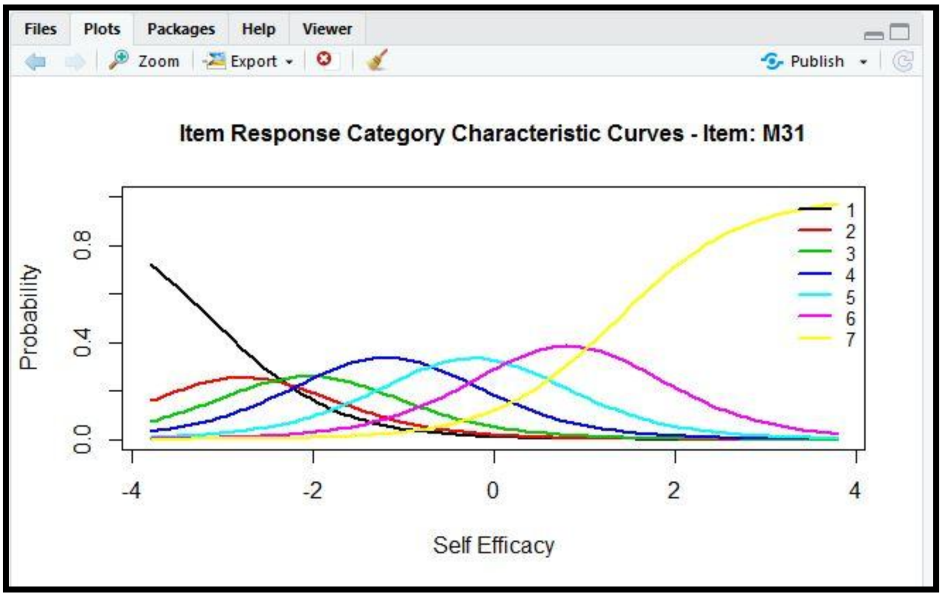


Figure 4.141 **Item Characteristic Curve (ICC)– M31**

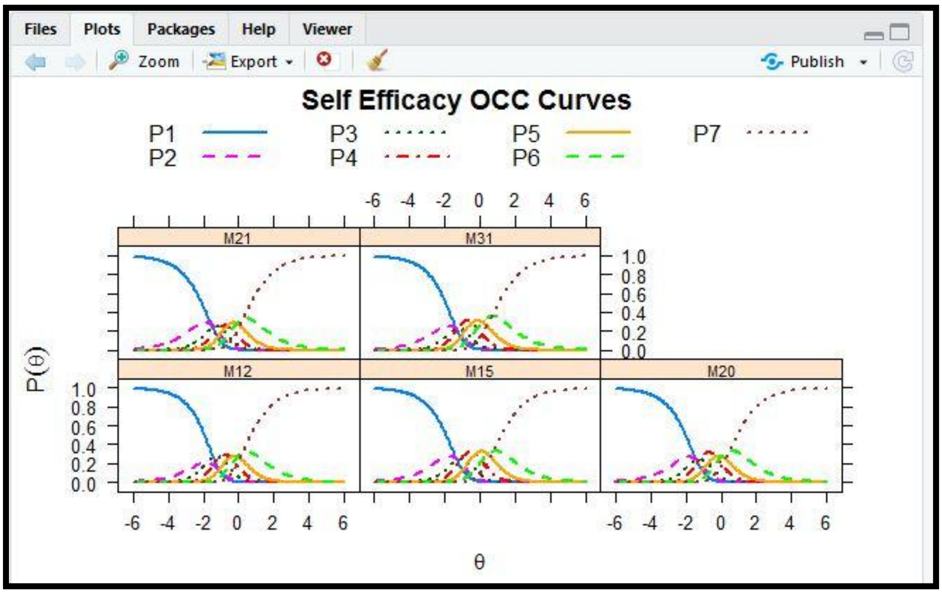


Figure 4.142 **Option Characteristic Curve (OCC)– Self Efficacy**

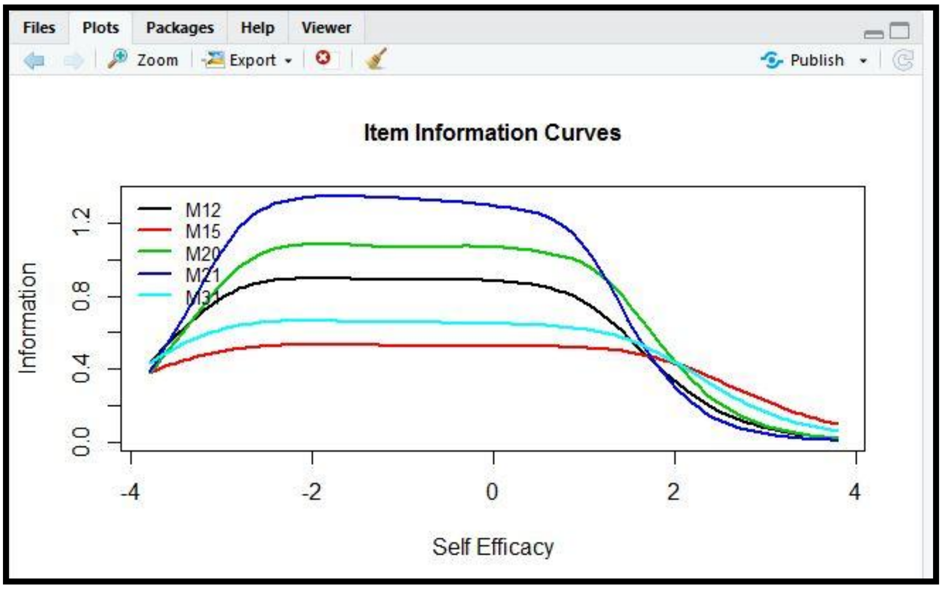


Figure 4.143 **Item Information Curve (IIC)– Self Efficacy**

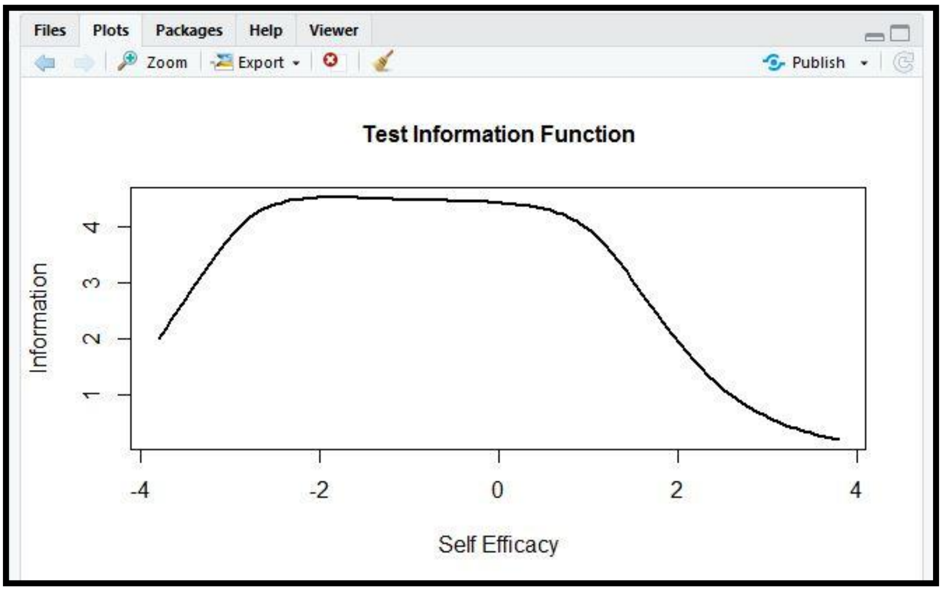


Figure 4.144 **Test Information Curve (TIC)– Self Efficacy**

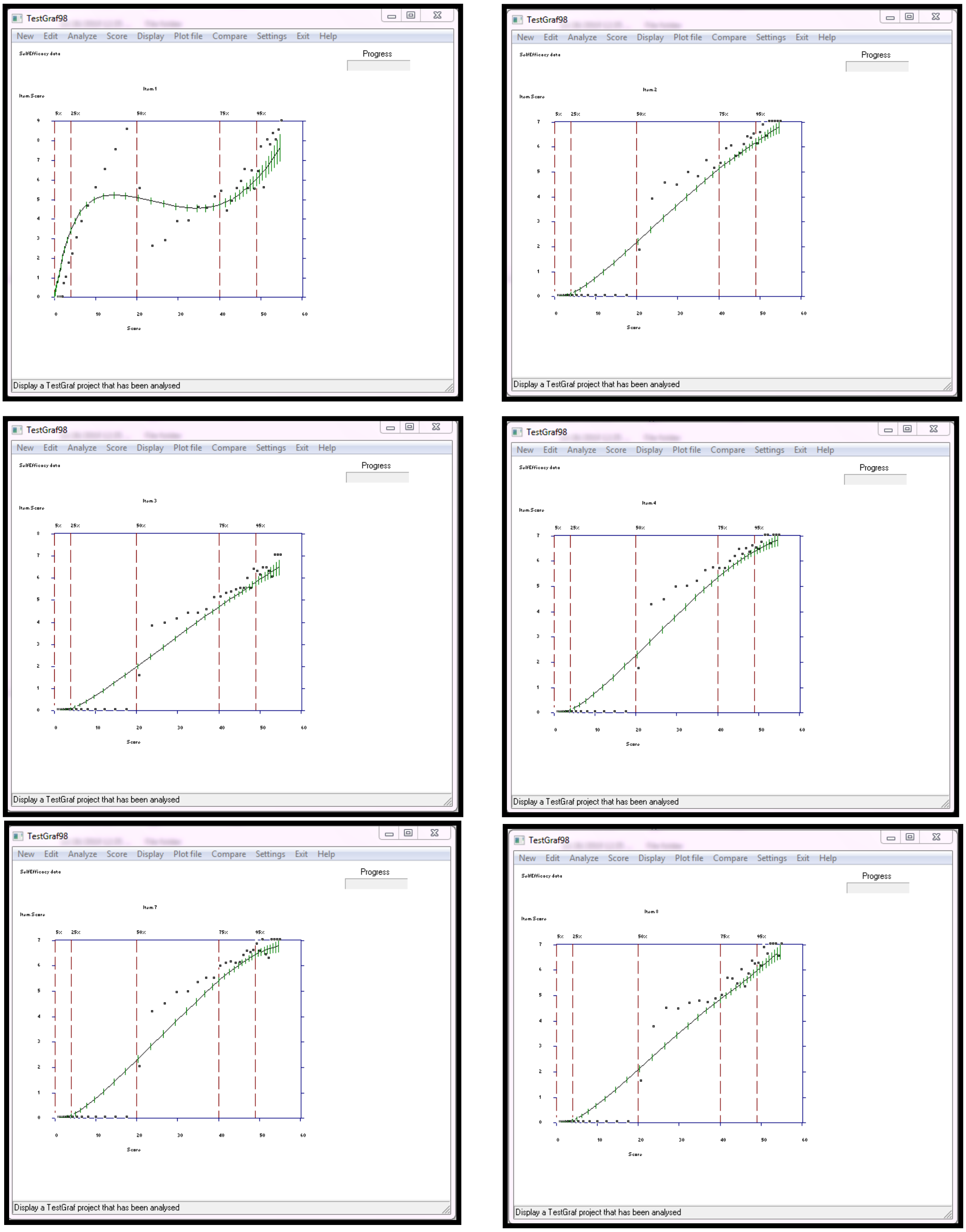
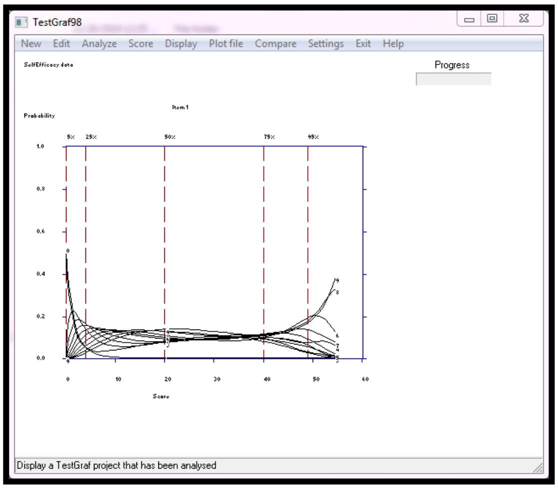
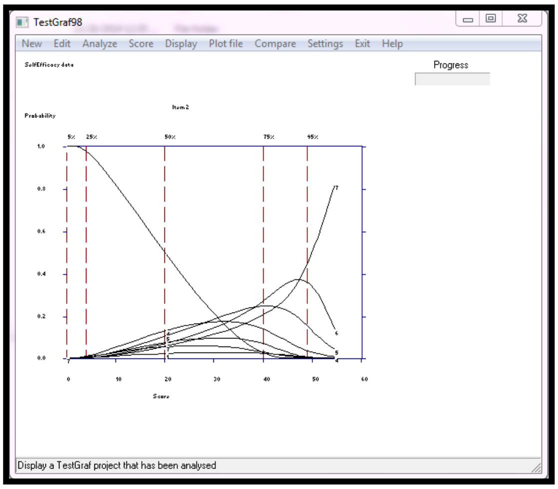
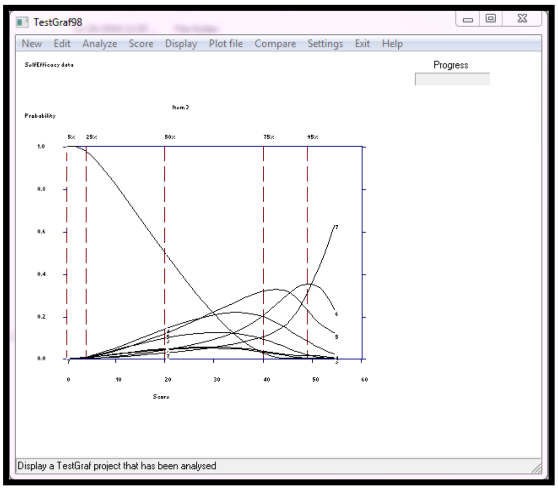


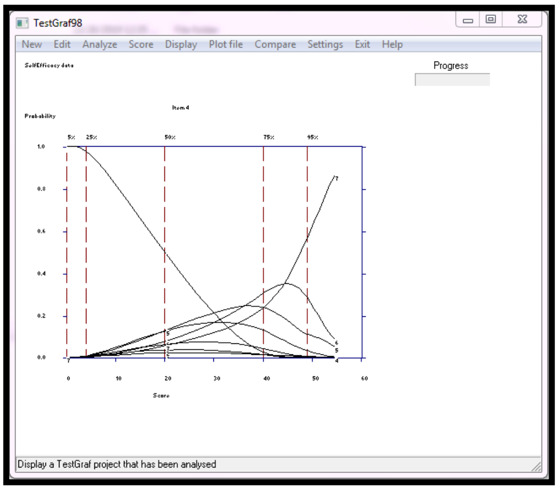
Figure 4.145 **Non-Parametric Item Characteristics Curve (ICC) for Self Efficacy Items Using TestGraf98:**

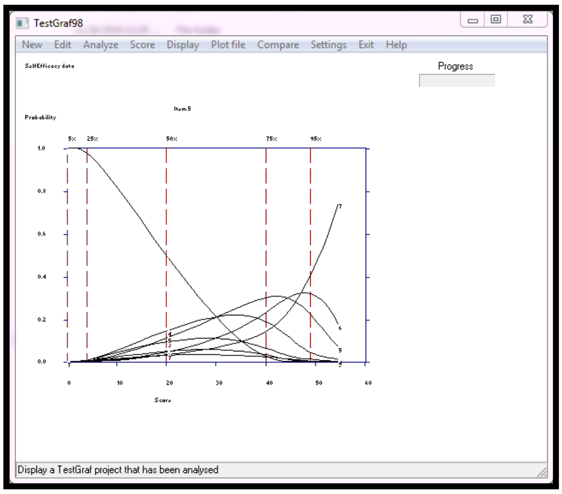
Interpretation: The non-parametric item characteristic curve of item1 is not monotonus and hence the item should be removed from the scale.


TestGraf98
New Edit Analyze Score Display Plot file Compare Settings Exit Help
Progress
Display a TestGraf project that has been analysed


TestGraf98
New Edit Analyze Score Display Plot file Compare Settings Exit Help
Progress
Display a TestGraf project that has been analysed


TestGraf98
New Edit Analyze Score Display Plot file Compare Settings Exit Help
Progress
Display a TestGraf project that has been analysed


TestGraf98
New Edit Analyze Score Display Plot file Compare Settings Exit Help
Progress
Display a TestGraf project that has been analysed


TestGraf98
New Edit Analyze Score Display Plot file Compare Settings Exit Help
Progress
Display a TestGraf project that has been analysed

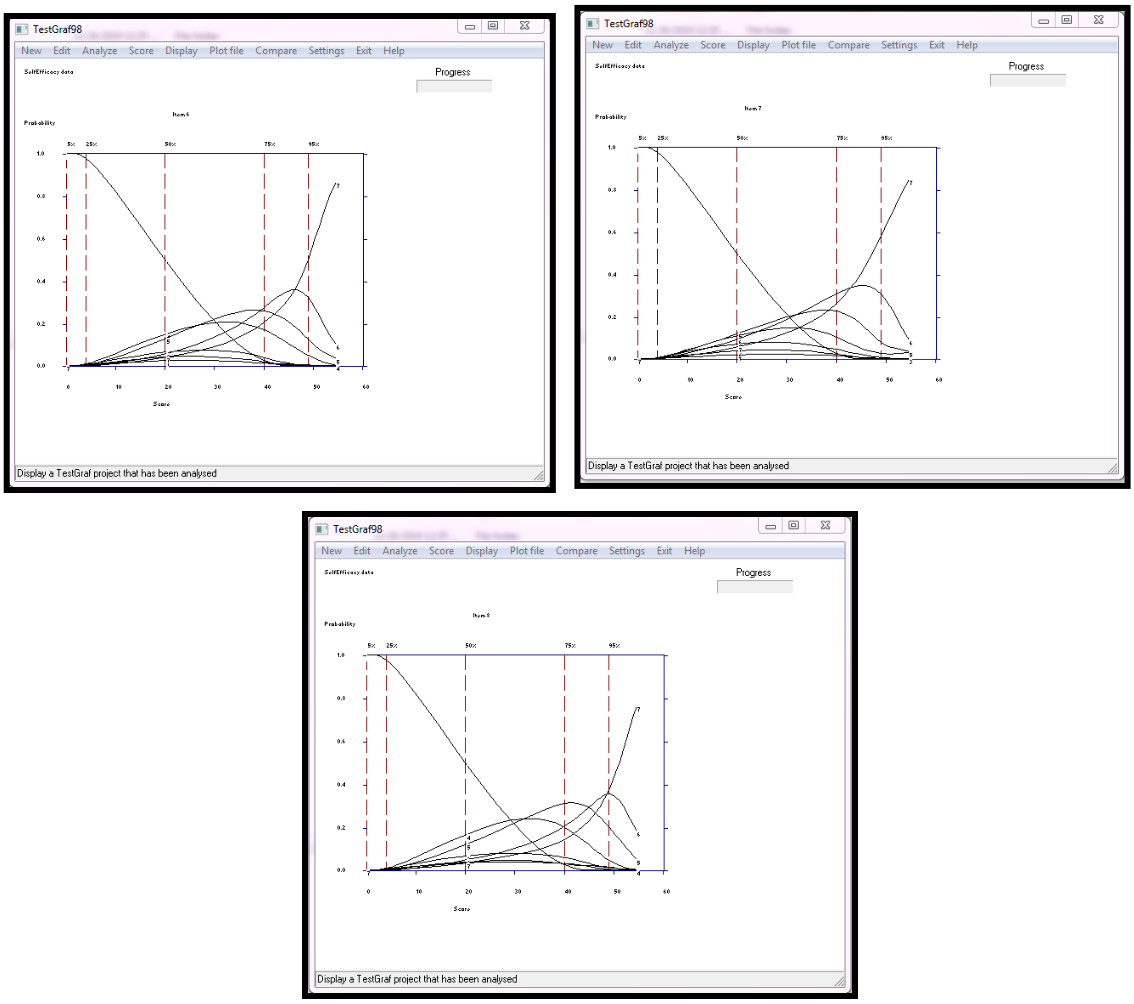


Figure 4.146 **Non Parametric Option Characteristic Curves (OCC) Self Efficacy Items using TestGraf98:**

8. Items and Options Performance of Scale Eight – Goal Orientation:

```
> library(haven)
> Goal_Orientation <- read_sav("D:/Item Discrimination of Final Tool Items in R/MLSQ/Go
al Orientation.sav")
> View(Goal_Orientation)
> fit1 <- grm(Goal_Orientation, constrained = FALSE)
> fit1

Call:
grm(data = Goal_Orientation, constrained = FALSE)

Coefficients:
     Extrmt1  Extrmt2  Extrmt3  Extrmt4  Extrmt5  Extrmt6  Dscrmn
M1    -2.778   -2.115   -1.414   -0.556    0.150    0.890   1.403
M16   -2.844   -2.233   -1.389   -0.438    0.391    1.265   1.624
M22   -3.136   -2.521   -1.669   -0.784    0.073    0.936   1.662
M24   -2.975   -2.325   -1.457   -0.483    0.557    1.625   1.282

Log.Lik: -12057.04

> 
```

Figure 4.147 **Item Discrimination Report – Goal Orientation**

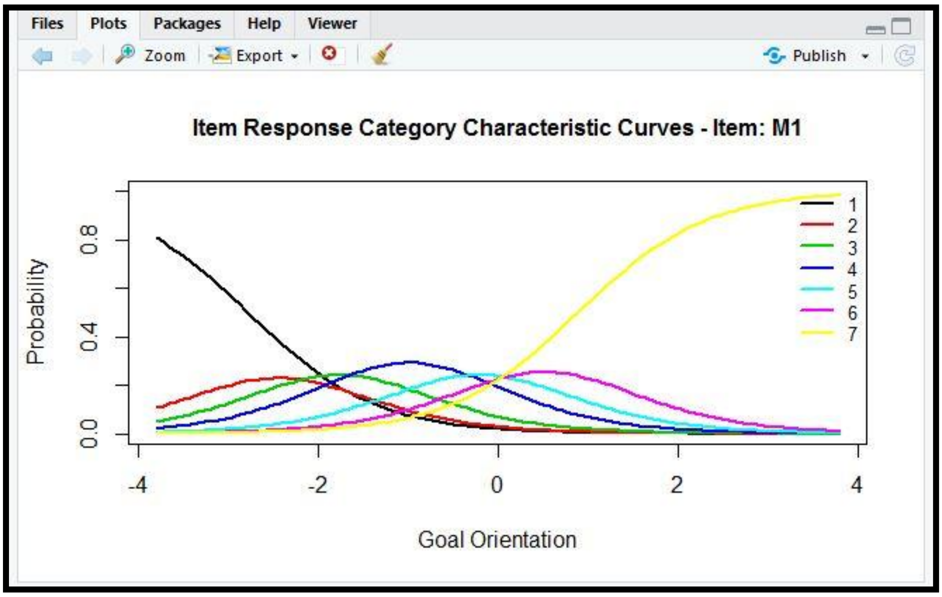


Figure 4.148 **Item Characteristic Curves (ICC) –M1**

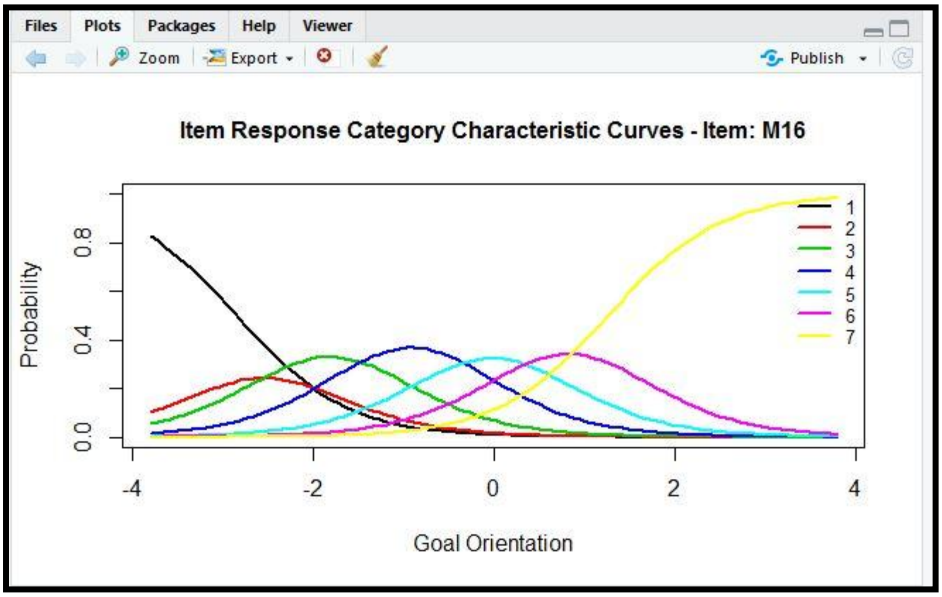


Figure 4.149 **Item Characteristic Curves (ICC) –M16**

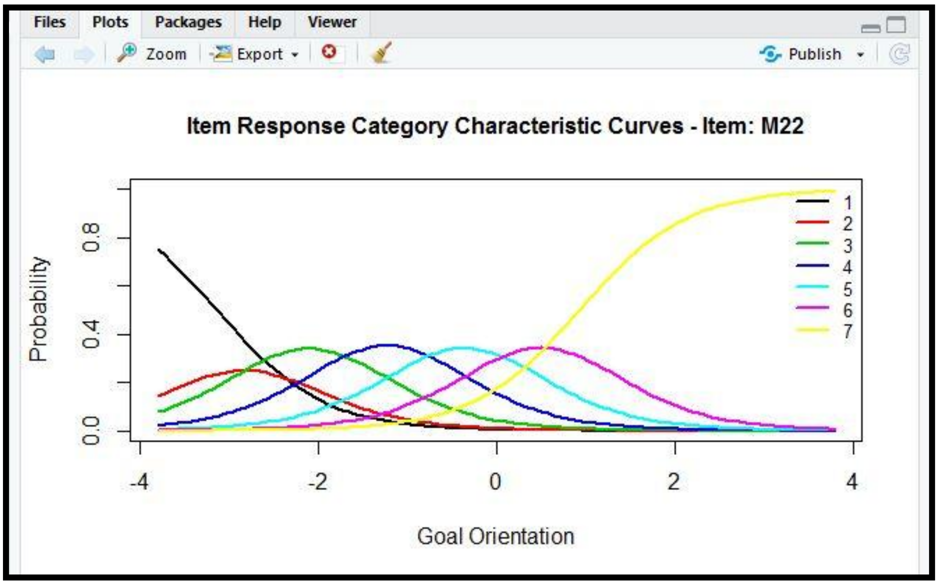


Figure 4.150 **Item Characteristic Curves (ICC) –M22**

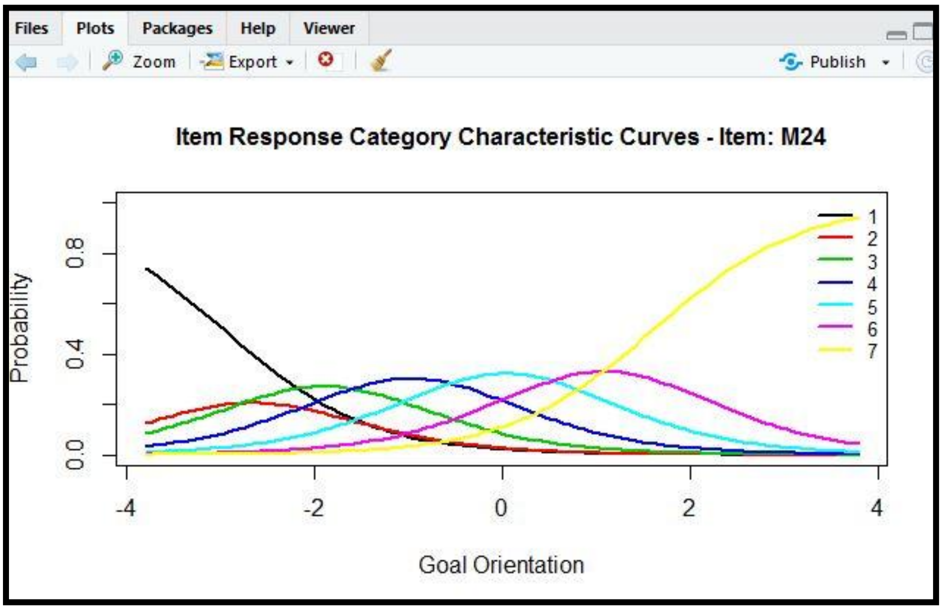


*Figure 4.151***Item Characteristic Curve (ICC) –M24**

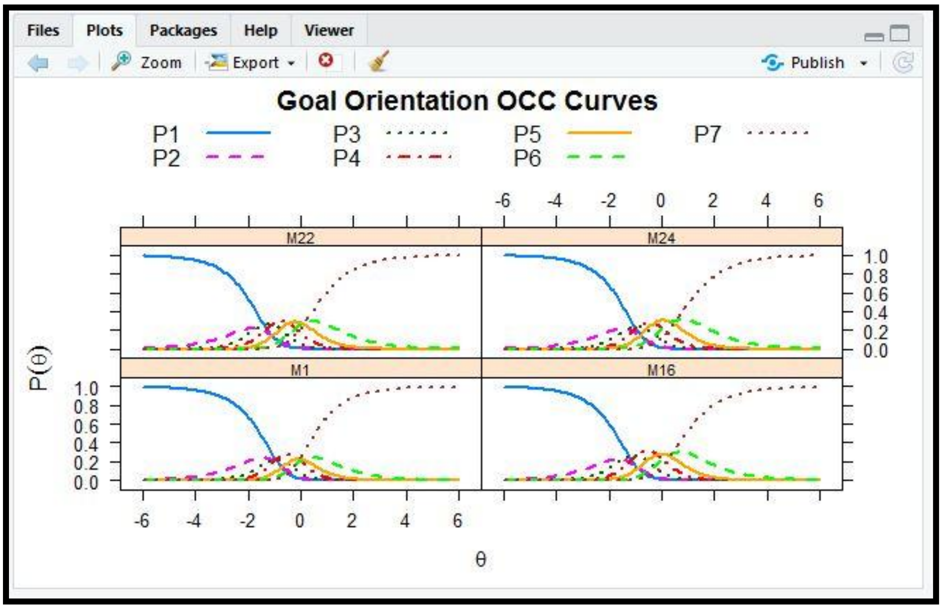


Figure 4.152 **Option Characteristic Curves (OCC) –Goal Orientation**

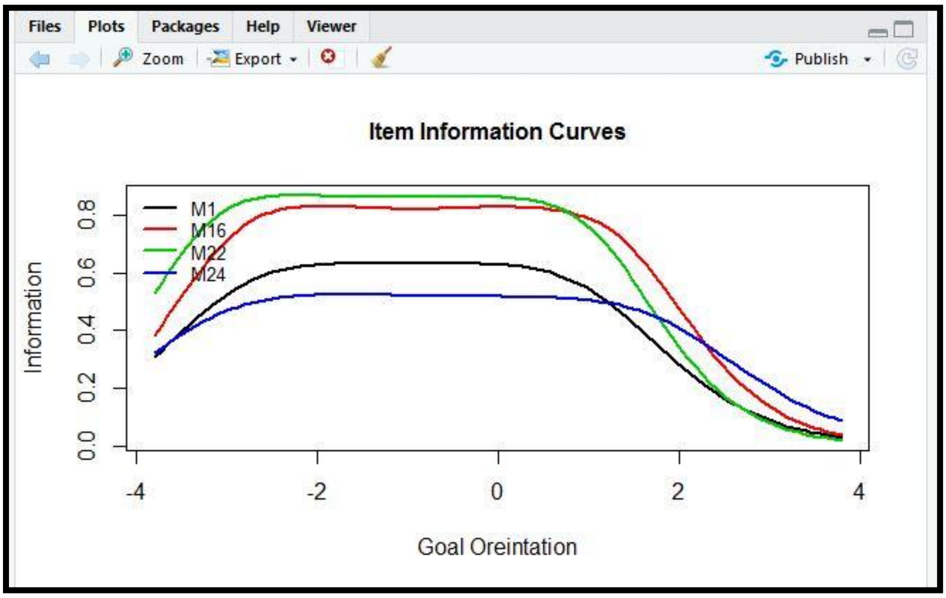


*Figure 4.153***Item Information Curve (IIC) –Goal Orientation**

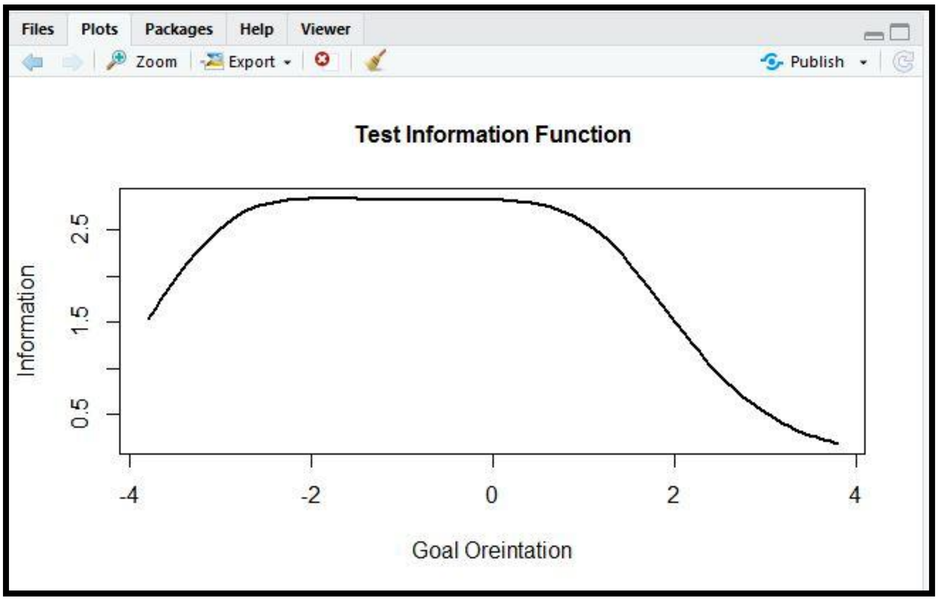


Figure 4.154 **Test Information Curve (TIC) –Goal Orientation**

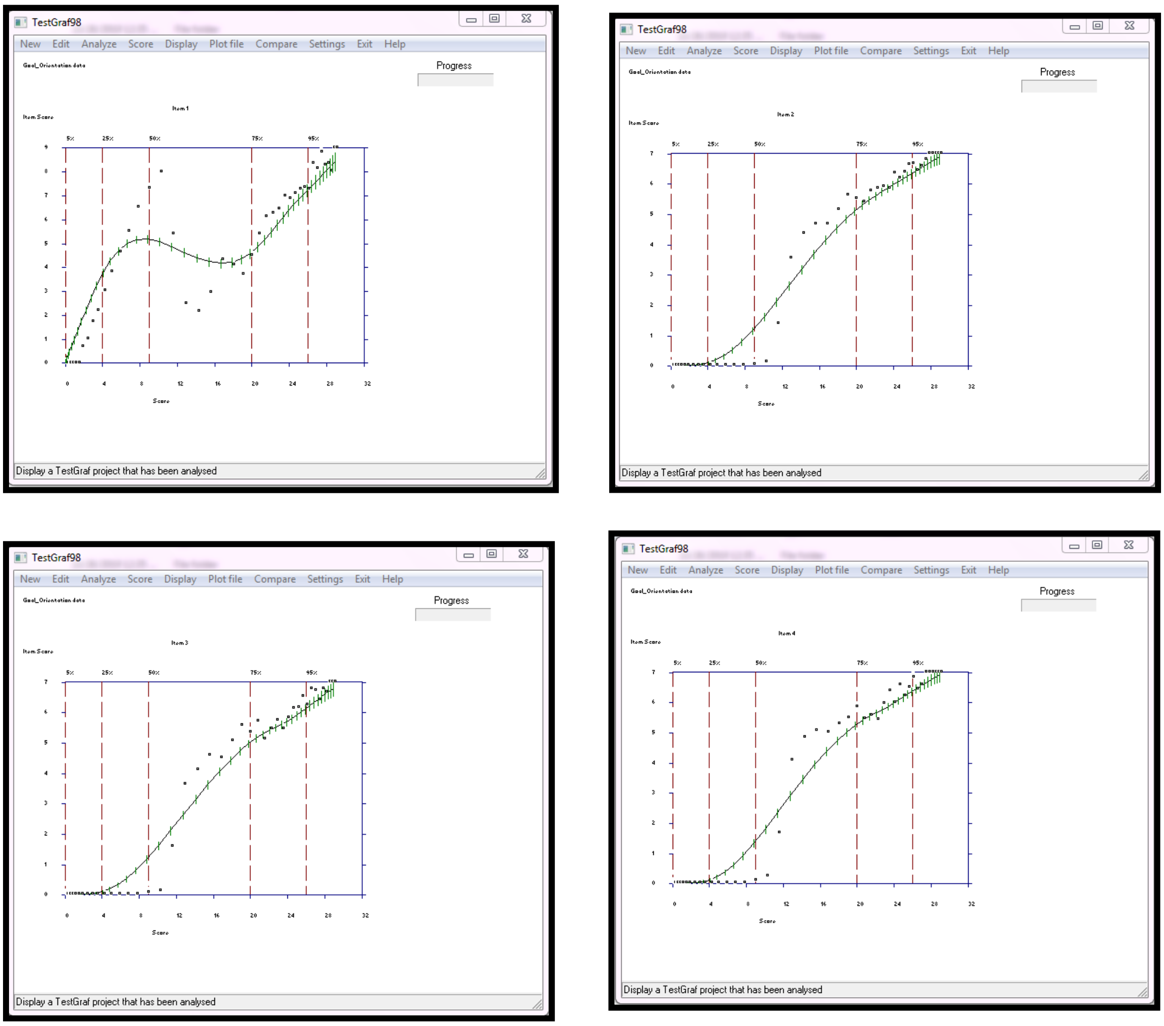


Figure 4.155 **Non-Parametric Item Characteristics Curve (ICC) for Goal Orientation Items Using TestGraf98:**

Interpretation: The first item of goal orientation scale should be eliminated since it is not monotonous in nature and does not satisfy the vital assumption of non-parametric item response theory.

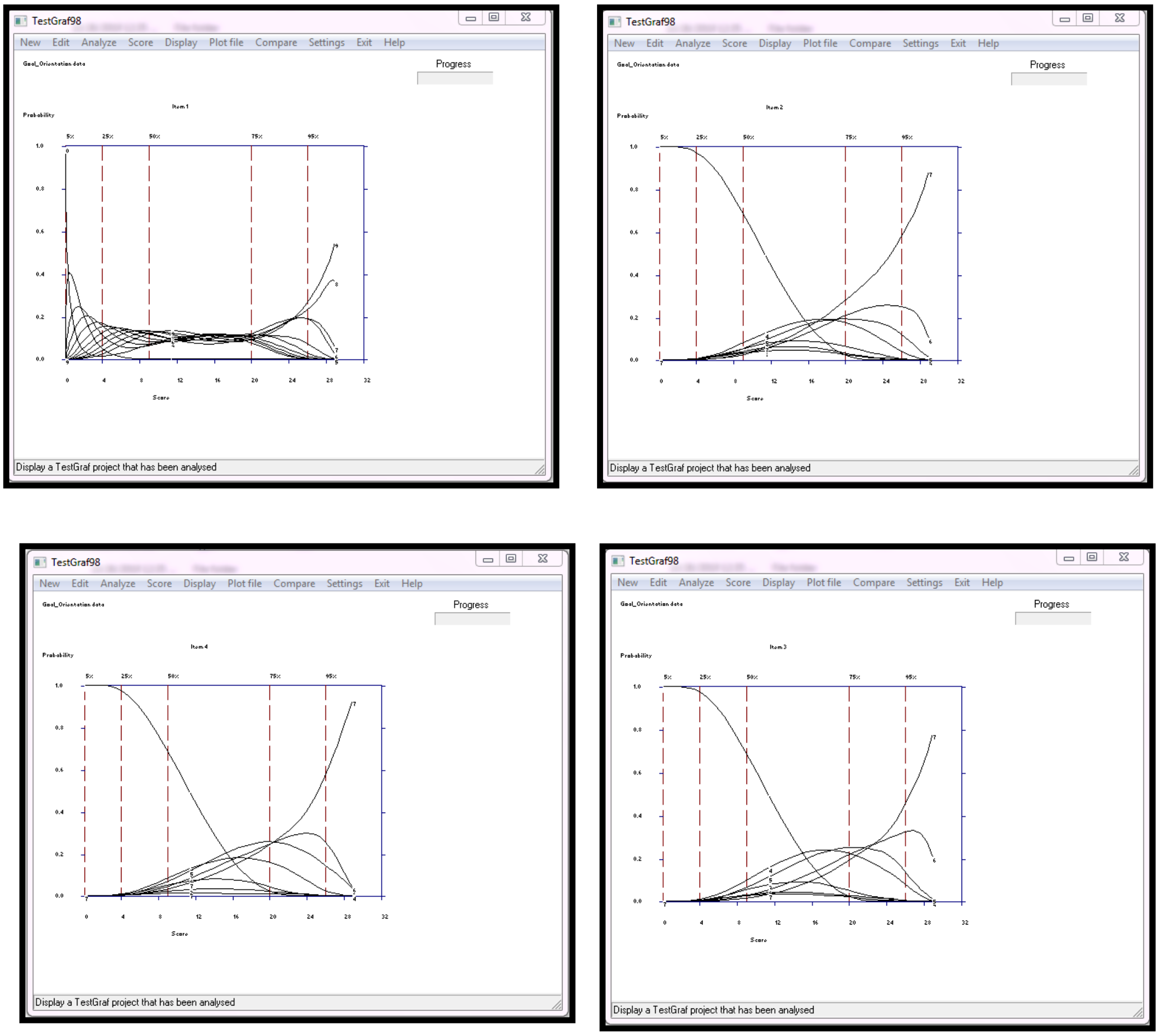


Figure 4.156 **Non Parametric Option Characteristic Curves (OCC) Goal Orientation Items using TestGraf98:**

9. Items and Options Performance of Scale Nine – Academic Delay of Gratification Scale:

```
Call:
grm(data = ADGS_DATA, constrained = FALSE)

Coefficients:
$ADGS1
Extrmt1  Extrmt2  Extrmt3  Extrmt4   Dscrmn
 -1.607   -0.189    1.189    4.753    1.295

$ADGS2
Extrmt1  Extrmt2  Extrmt3   Dscrmn
  1.852   -0.701   -3.825   -0.523

$ADGS3
Extrmt1  Extrmt2  Extrmt3   Dscrmn
 -0.966   -0.005    1.106    1.430

$ADGS4
Extrmt1  Extrmt2  Extrmt3   Dscrmn
 -1.438   -0.679    0.298    1.910

$ADGS5
Extrmt1  Extrmt2  Extrmt3   Dscrmn
 -1.762   -0.320    1.447    0.888

$ADGS6
Extrmt1  Extrmt2  Extrmt3   Dscrmn
 -1.127   -0.117    1.171    1.113

$ADGS7
Extrmt1  Extrmt2  Extrmt3   Dscrmn
  1.623   -0.391   -2.091   -0.777
```

Figure 4.157 **Item Discrimination Report – Original Scale – ADGS – Item 1 to**

```
$ADGS7
Extrmt1  Extrmt2  Extrmt3   Dscrmn
  1.623   -0.391   -2.091   -0.777

$ADGS8
Extrmt1  Extrmt2  Extrmt3   Dscrmn
 -2.186   -0.885    0.305    1.361

$ADGS9
Extrmt1  Extrmt2  Extrmt3   Dscrmn
 -1.516   -0.085    1.458    1.077

$ADGS10
Extrmt1  Extrmt2  Extrmt3   Dscrmn
 -1.672   -0.566    0.761    1.501

$Gender
Extrmt1   Dscrmn
100.941   -0.017


Log.Lik: -2457.778
```

Figure 4.158 **Item Discrimination Report – Original Scale – ADGS – Item 8 -**

```
Call:
grm(data = ADGS_DATA_Copy, constrained = FALSE)

Coefficients:
$ADGS4
Extrmt1  Extrmt2  Extrmt3   Dscrmn
 -1.646   -0.769    0.354    1.501

$ADGS5
Extrmt1  Extrmt2  Extrmt3   Dscrmn
 -1.705   -0.342    1.363    0.953

$ADGS8
Extrmt1  Extrmt2  Extrmt3   Dscrmn
 -1.781   -0.758    0.235    2.072

$ADGS9
Extrmt1  Extrmt2  Extrmt3   Dscrmn
 -1.545   -0.105    1.458    1.067

$ADGS10
Extrmt1  Extrmt2  Extrmt3   Dscrmn
 -1.536   -0.534    0.693    1.792

$Gender
 Extrmt1    Dscrmn
-133.231     0.013


Log.Lik: -1242.509
```

Figure 4.159 **Item Discrimination Report – Parsimonious Scale – ADGS**

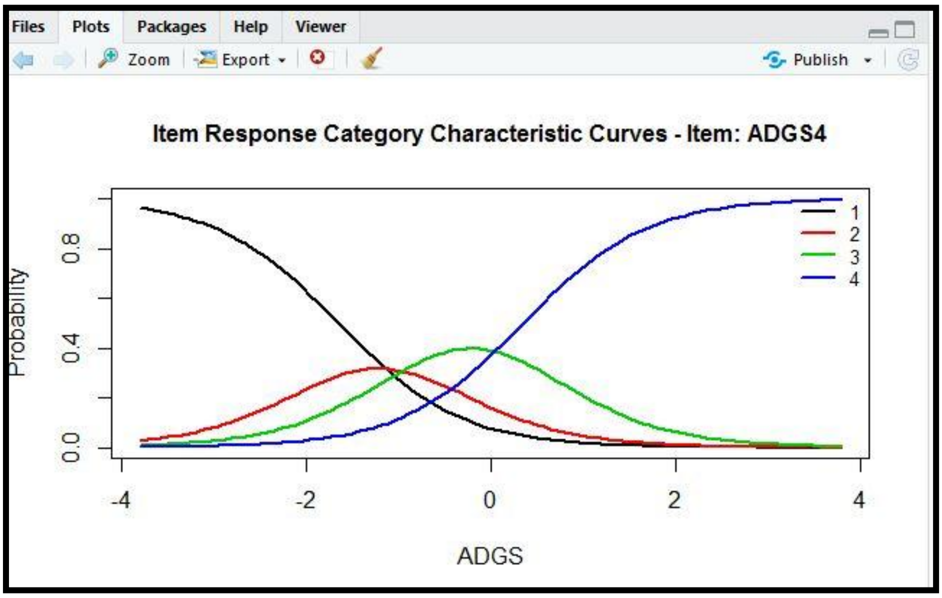


Figure 4.160 **Item Characteristic Curve (ICC) – ADGS4**

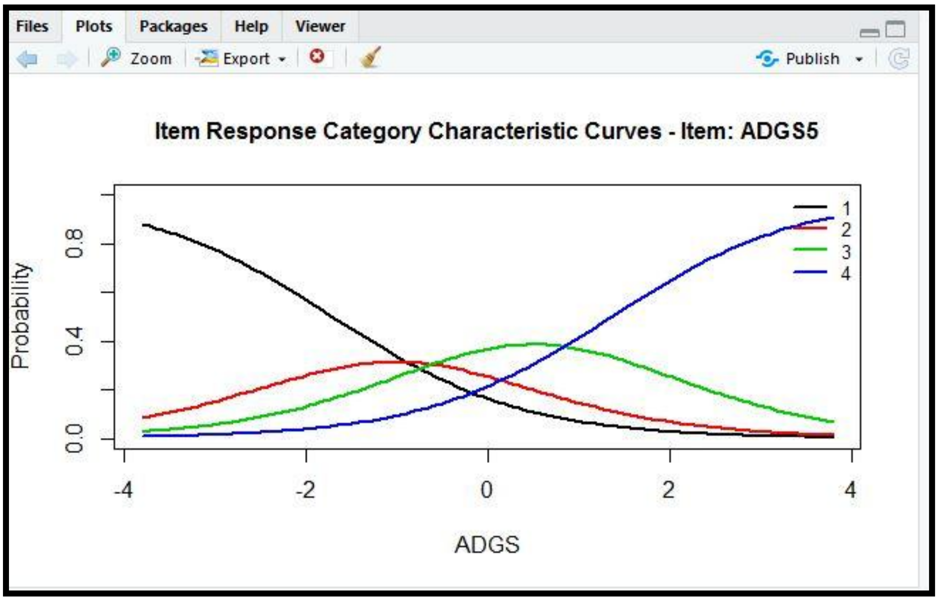


Figure 4.161 **Item Characteristic Curve (ICC) – ADGS5**

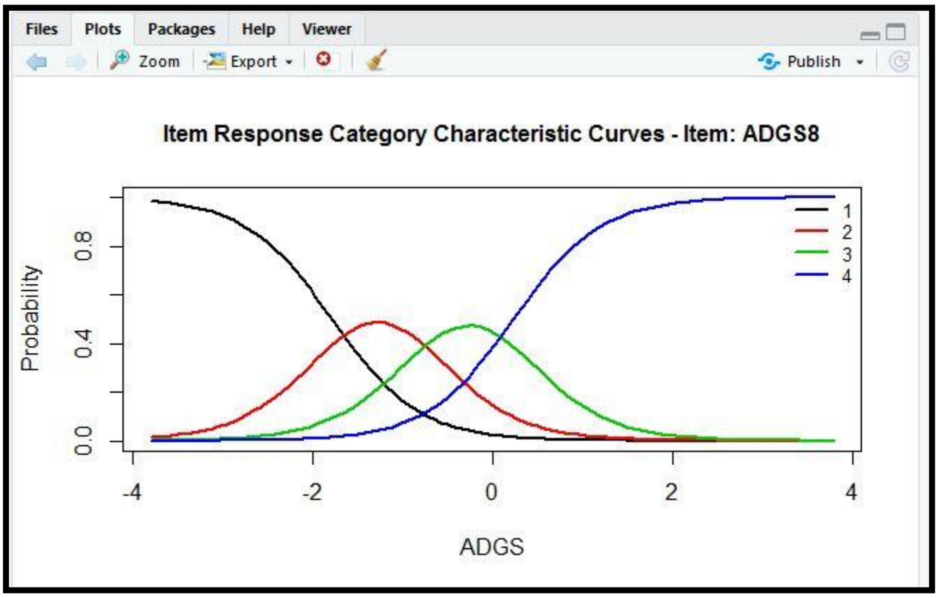


Figure 4.162 **Item Characteristic Curve (ICC) – ADGS8**

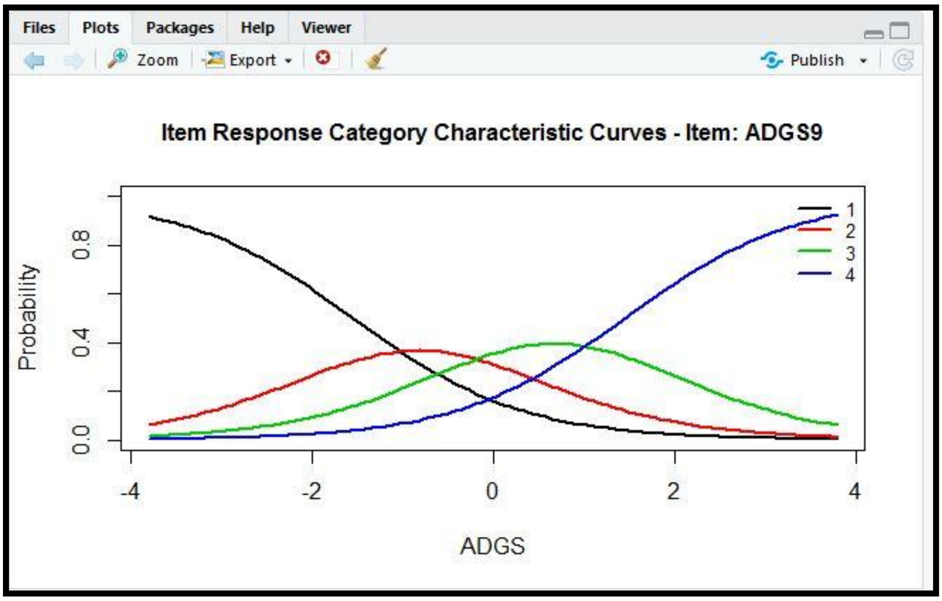


Figure 4.163 **Item Characteristic Curve (ICC) – ADGS9**

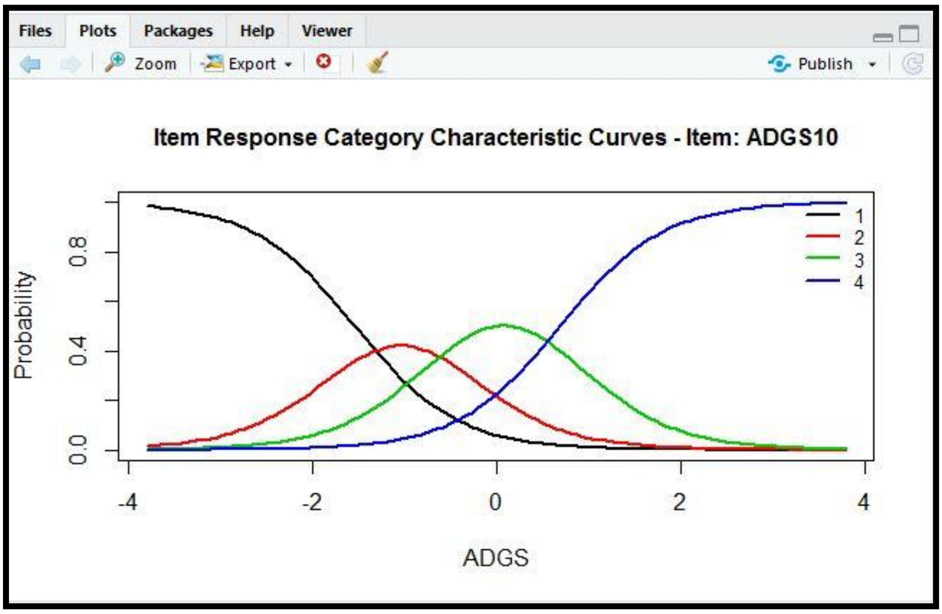


Figure 4.164 **Item Characteristic Curve (ICC) – ADGS10**

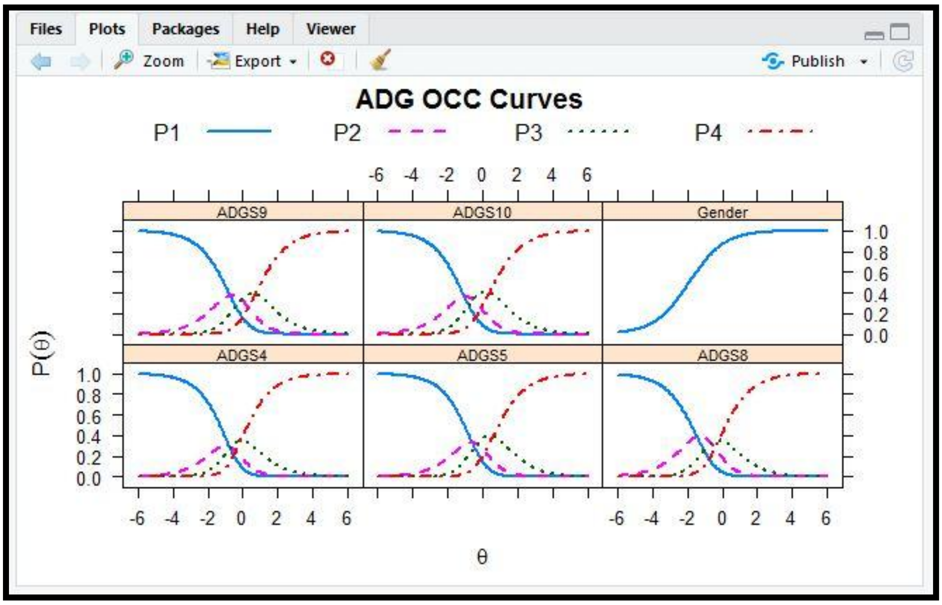


Figure 4.165 **Option Characteristic Curve (OCC) – ADGS**

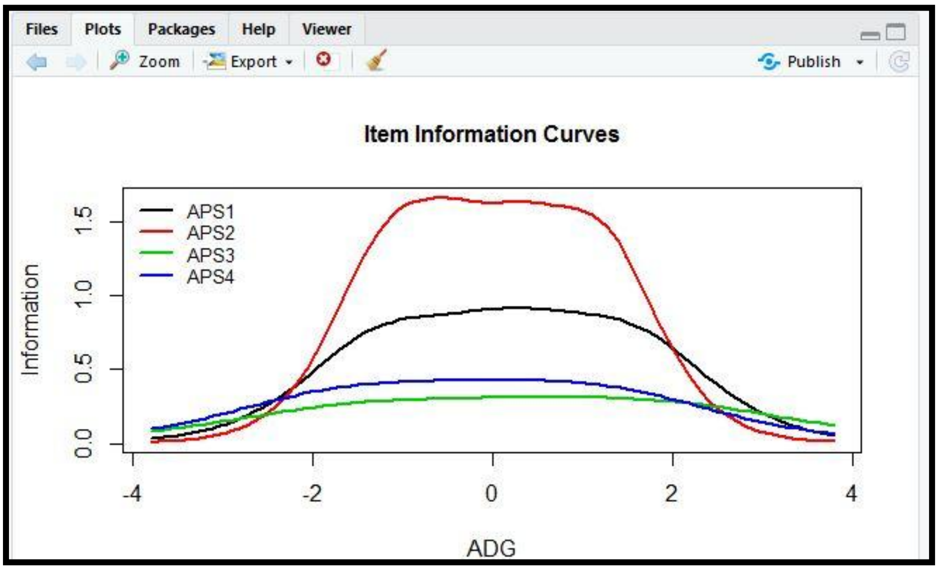


***Figure 4.166*Item Information Curve (IIC) – ADGS**

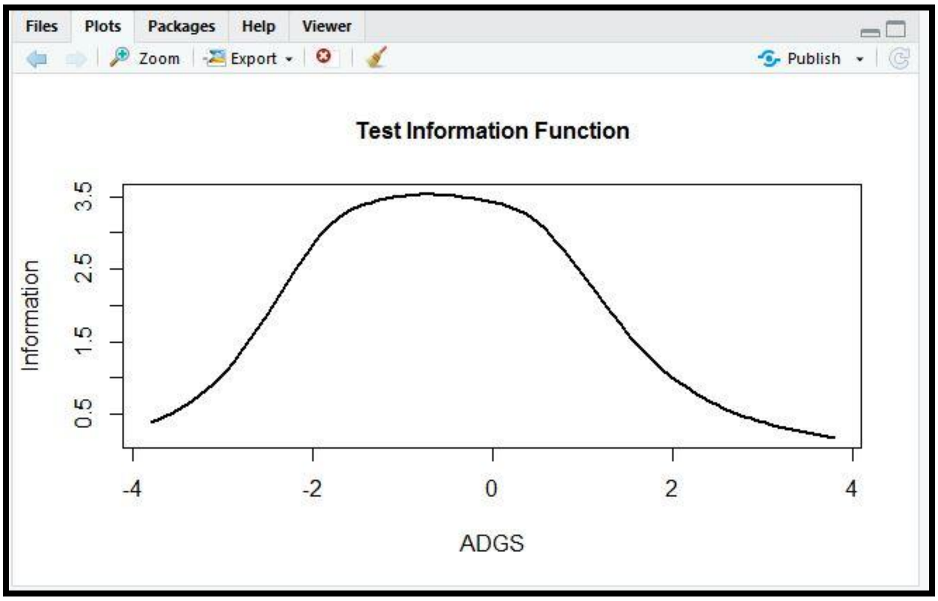
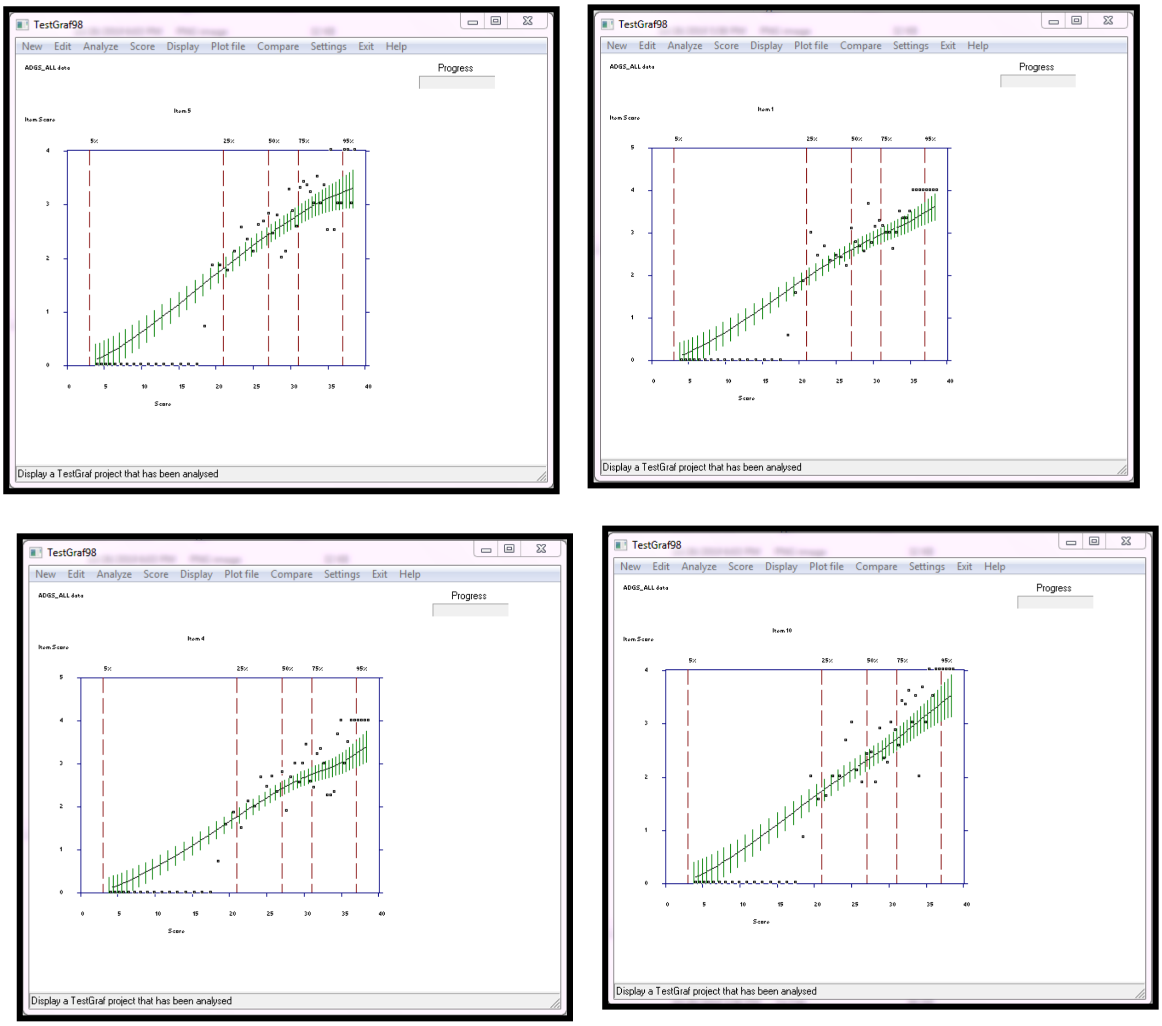


Figure 4.167**Test Information Curve (TIC) – ADGS**



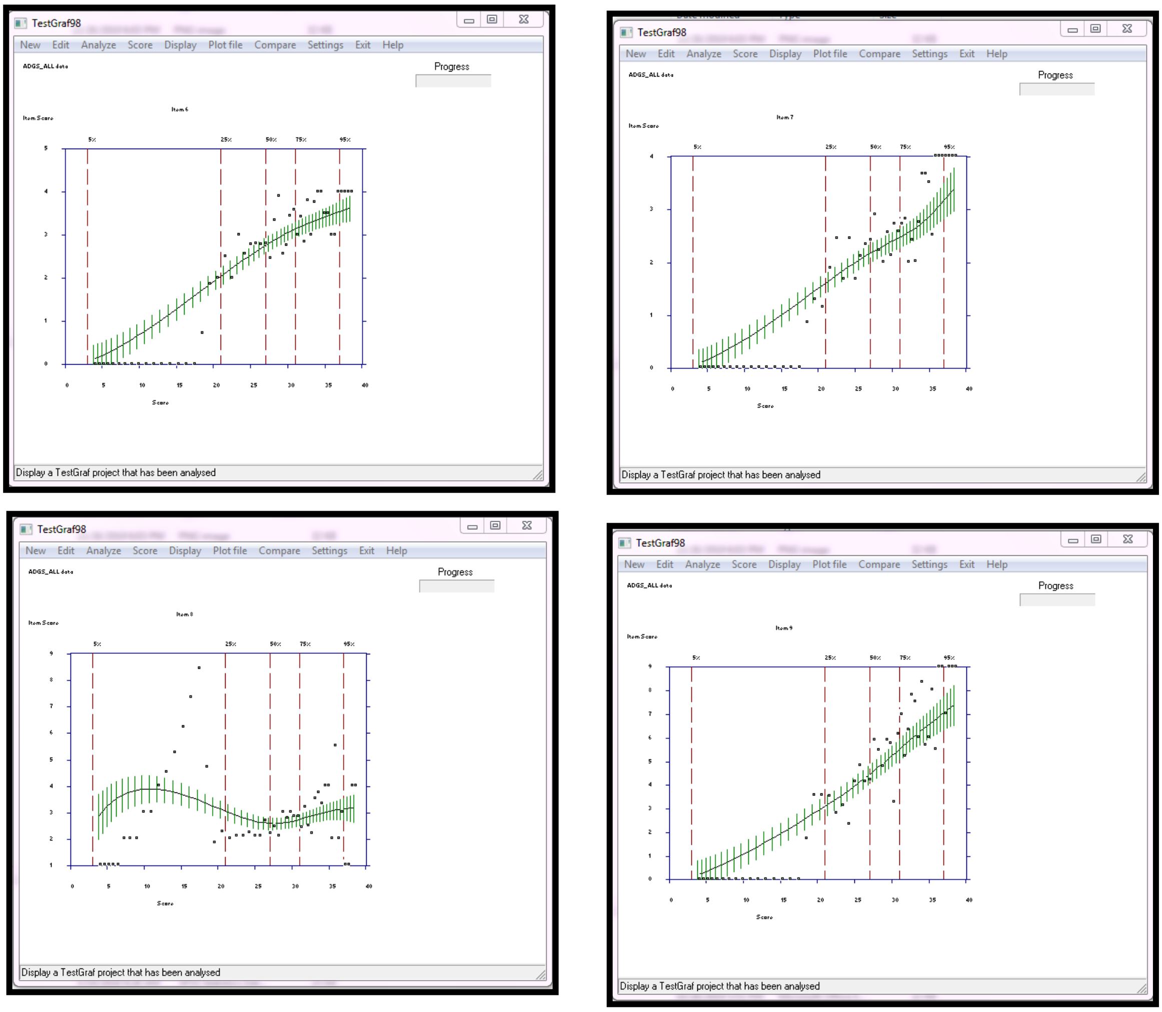
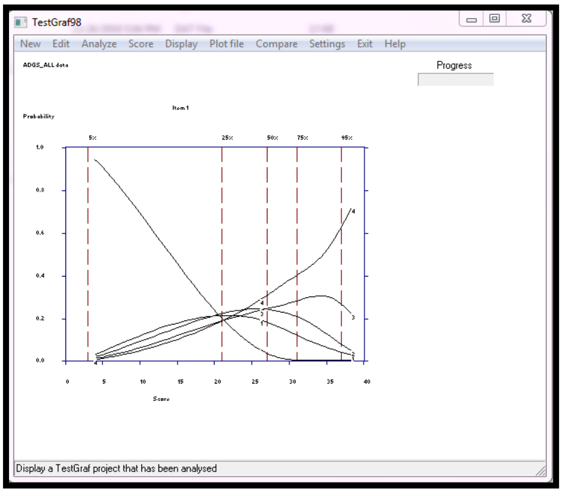
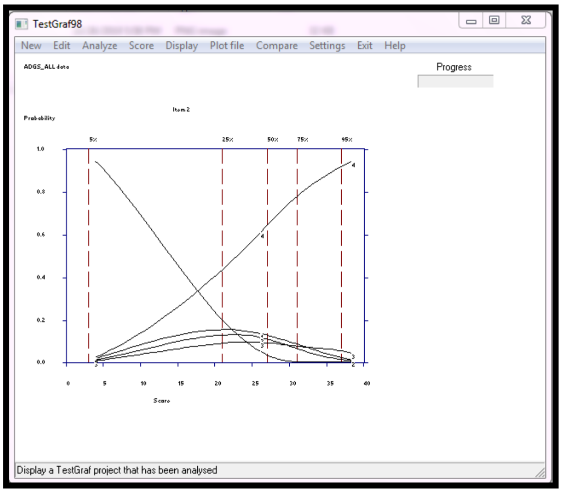
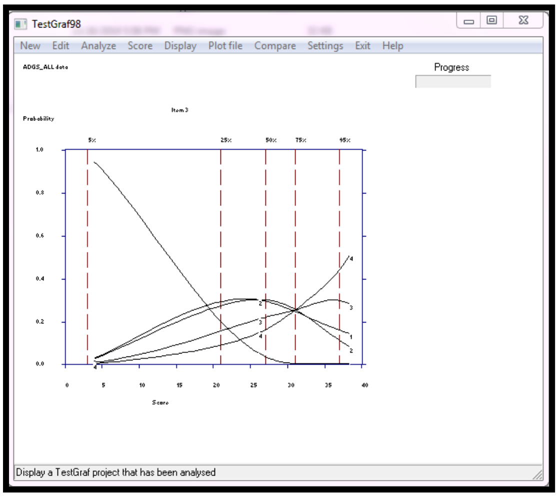


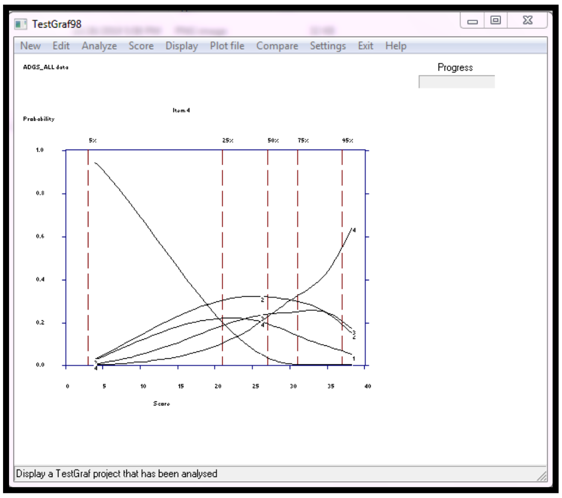
Figure 4.168 **Non-Parametric Item Characteristics Curve (ICC) for Academic Delay of Gratification Items Using TestGraf98:**

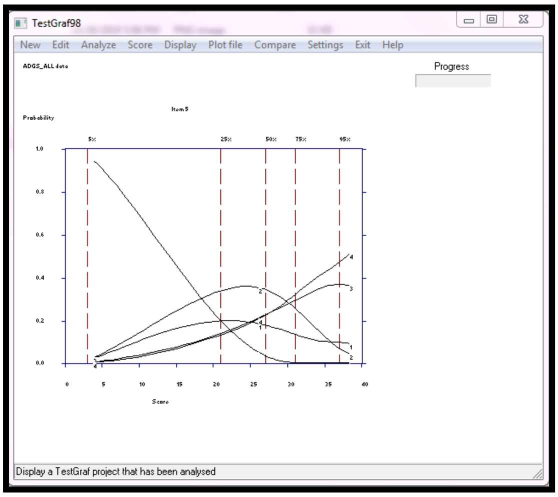
Interpretation: The ICC curve of item 8 is does not increase with the rise of ability of the respondants and hence is not monotonous satisfy the basic assumption of non-parametric item response theory based testing of items. Rest of the items have ICC which is fairly monotonous.

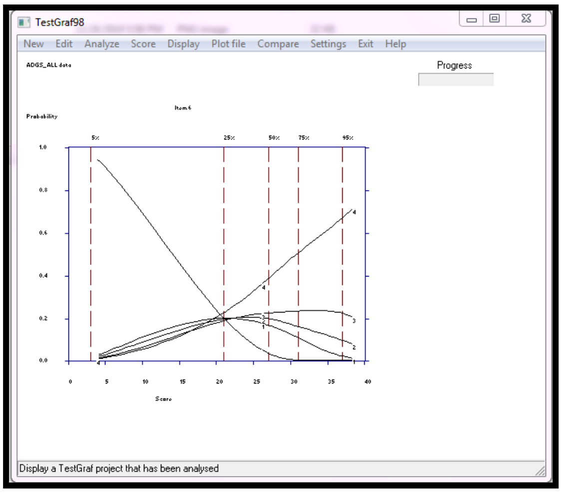

TestGraf98
New Edit Analyze Score Display Plot file Compare Settings Exit Help
Progress
Display a TestGraf project that has been analysed


TestGraf98
New Edit Analyze Score Display Plot file Compare Settings Exit Help
Progress
Display a TestGraf project that has been analysed


TestGraf98
New Edit Analyze Score Display Plot file Compare Settings Exit Help
Progress
Display a TestGraf project that has been analysed


TestGraf98
New Edit Analyze Score Display Plot file Compare Settings Exit Help
Progress
Display a TestGraf project that has been analysed


TestGraf98
New Edit Analyze Score Display Plot file Compare Settings Exit Help
Progress
Display a TestGraf project that has been analysed


TestGraf98
New Edit Analyze Score Display Plot file Compare Settings Exit Help
Progress
Display a TestGraf project that has been analysed

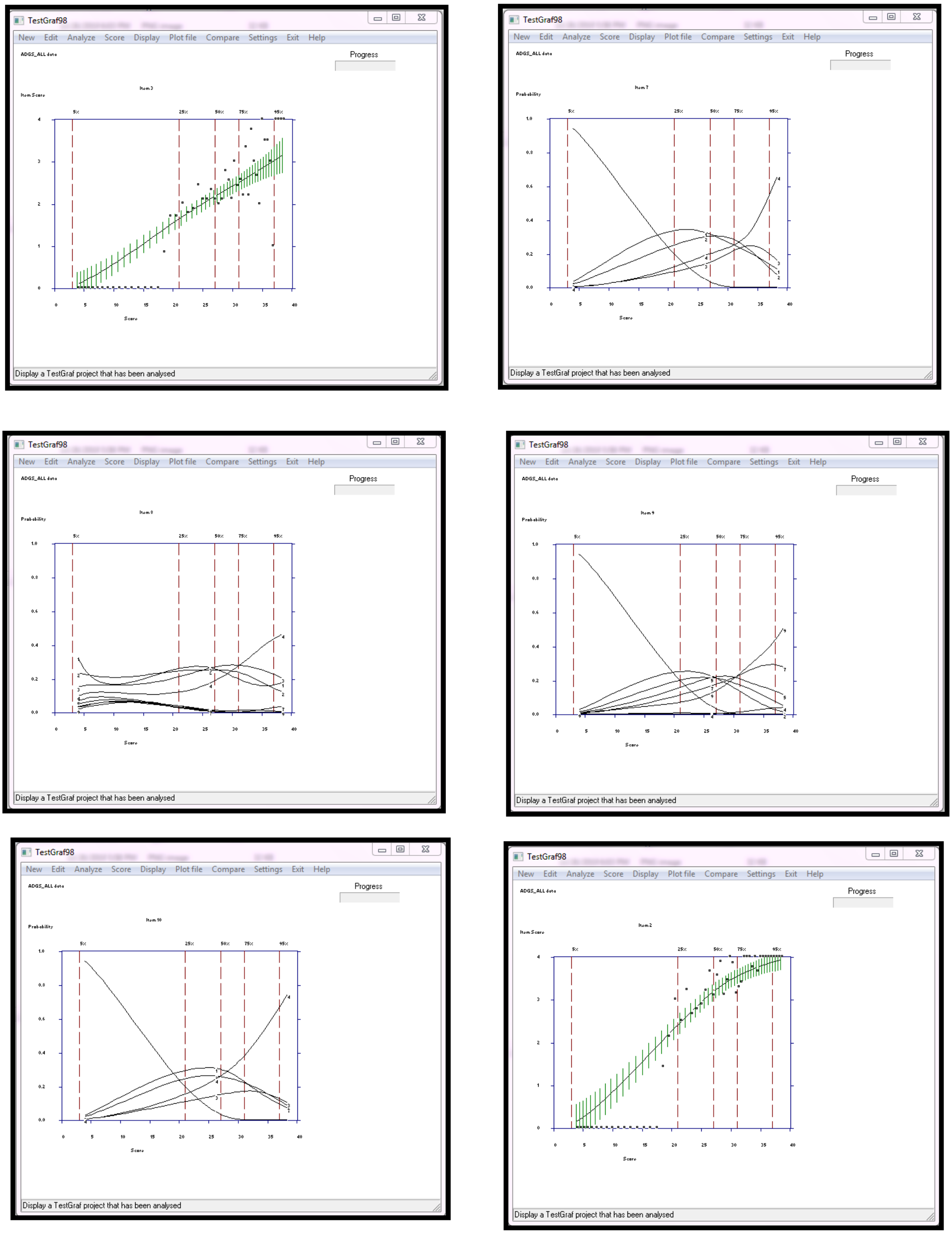


Figure 4.169 **Non Parametric Option Characteristic Curves (OCC) Academic Delay of Gratification Items using TestGraf9**8:

10. Items and Options Performance of Scale Ten – Academic Procrastination:

```
Call:
grm(data = AP_DATA_Copy, constrained = FALSE)

Coefficients:
      Extrmt1  Extrmt2  Extrmt3  Extrmt4  Dscrmn
APS1   -1.210   -0.100    0.520    1.543   1.715
APS2   -1.192   -0.478    0.389    1.272   2.040
APS3   -1.448    0.058    0.964    1.934   1.043
APS4   -1.596   -0.340    0.195    1.225   1.288
APS5   -2.317   -0.693    0.974    2.669   0.817

Log.Lik: -1405.618

> library(haven)
> AP_DATA_Copy <- read_sav("D:/Item Discrimination of Final Tool Items in R/AP_DA
opy.sav")
> View(AP_DATA_Copy)
> fit2 <- grm(AP_DATA_Copy, constrained = FALSE)
> fit2

Call:
grm(data = AP_DATA_Copy, constrained = FALSE)

Coefficients:
      Extrmt1  Extrmt2  Extrmt3  Extrmt4  Dscrmn
APS1   -1.216   -0.104    0.517    1.544   1.712
APS2   -1.138   -0.450    0.375    1.209   2.343
APS3   -1.501    0.056    1.001    2.013   0.994
APS4   -1.695   -0.358    0.211    1.309   1.167
```

Figure 4.170 **Item Discrimination Report – Academic Procrastination**

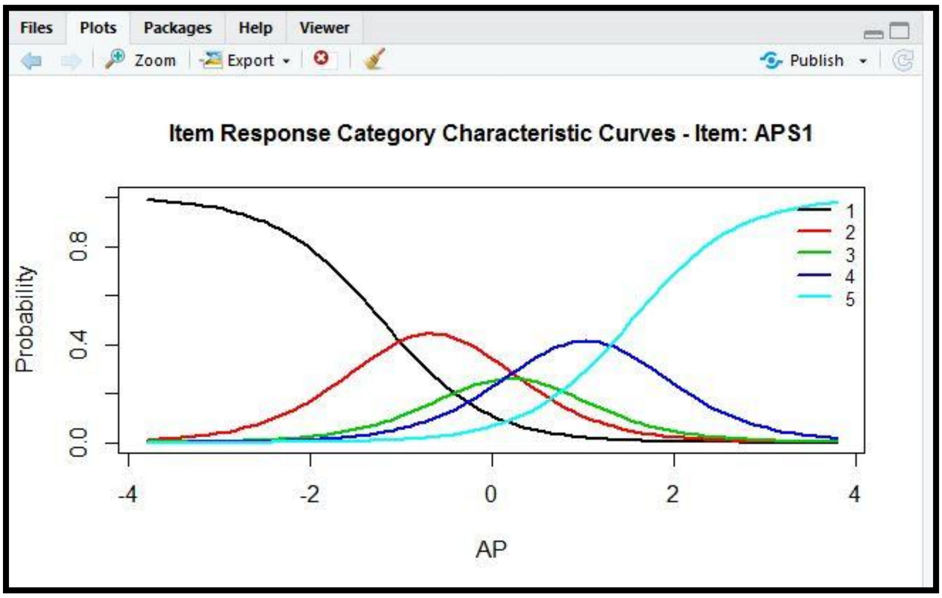


Figure 4.171 **Item Characteristic Curve (ICC) – APS1**

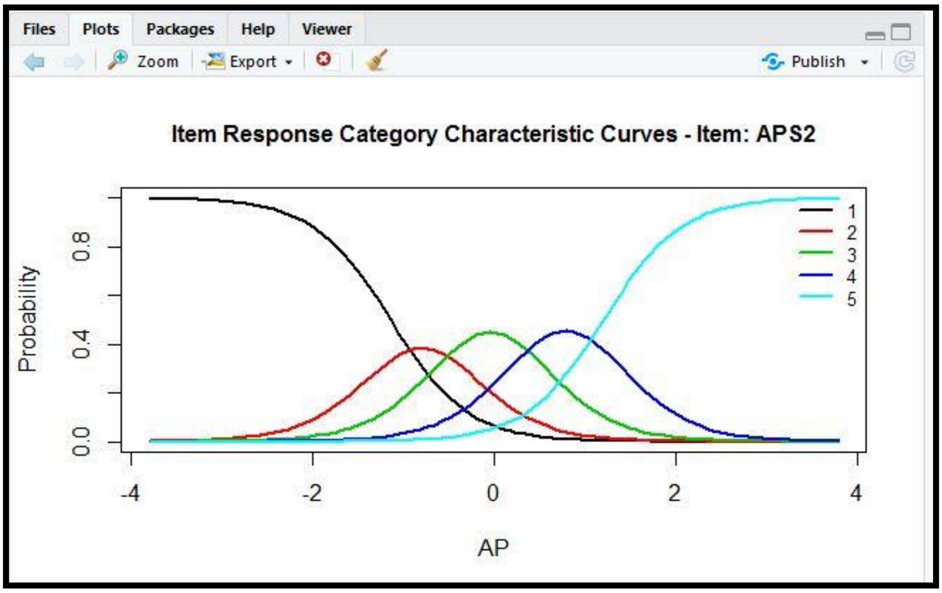


Figure 4.172 **Item Characteristic Curve (ICC) – APS2**

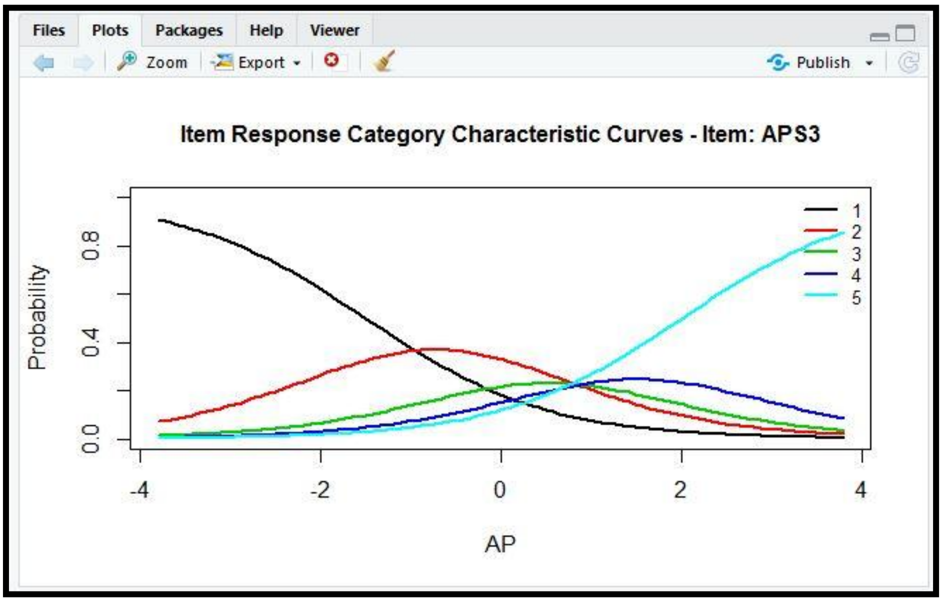


Figure 4.173 **Item Characteristic Curve (ICC) – APS3**

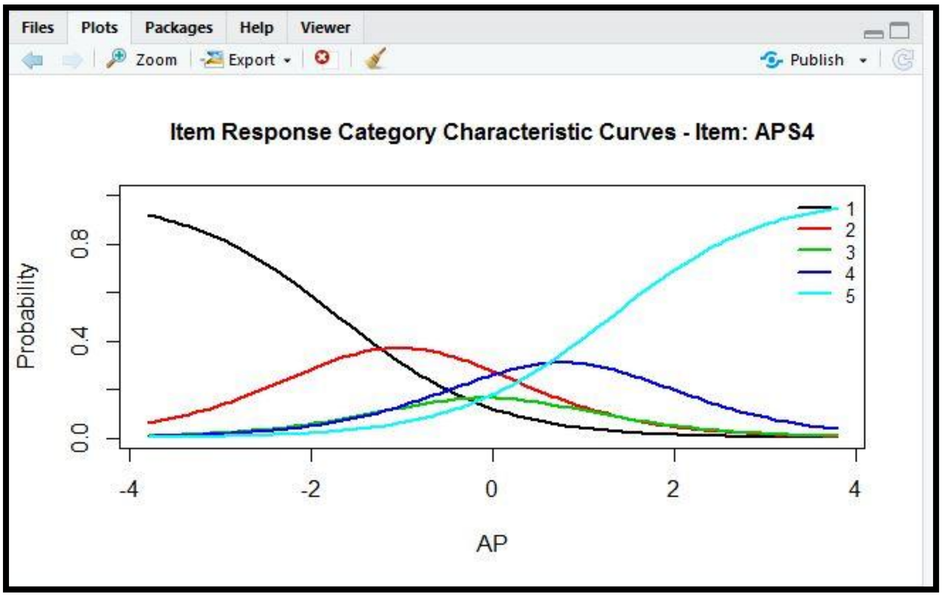


Figure 4.174 **Item Characteristic Curve (ICC) – APS4**

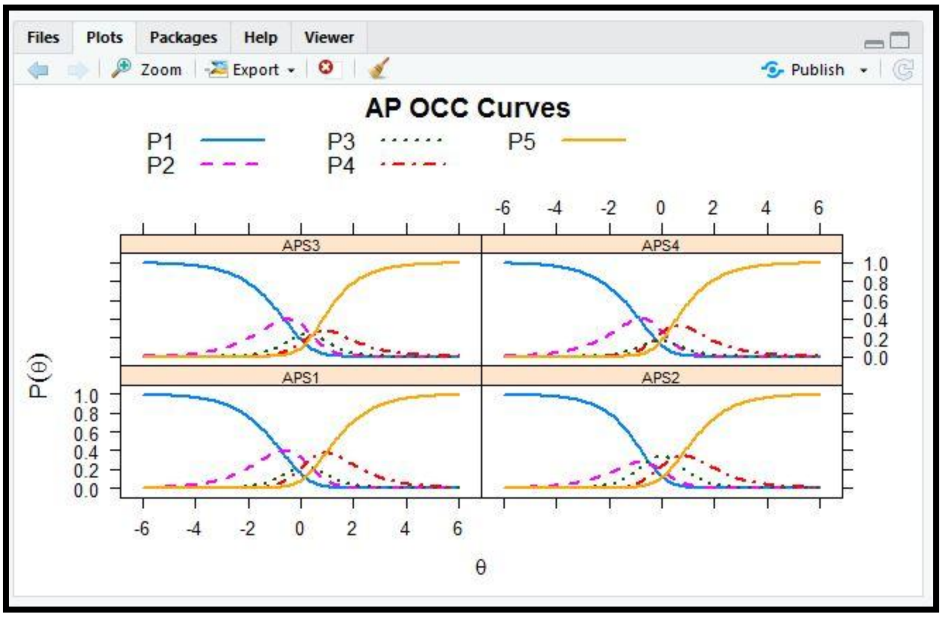


Figure 4.175 **Option Characteristic Curve (OCC) – Academic Procrastination**

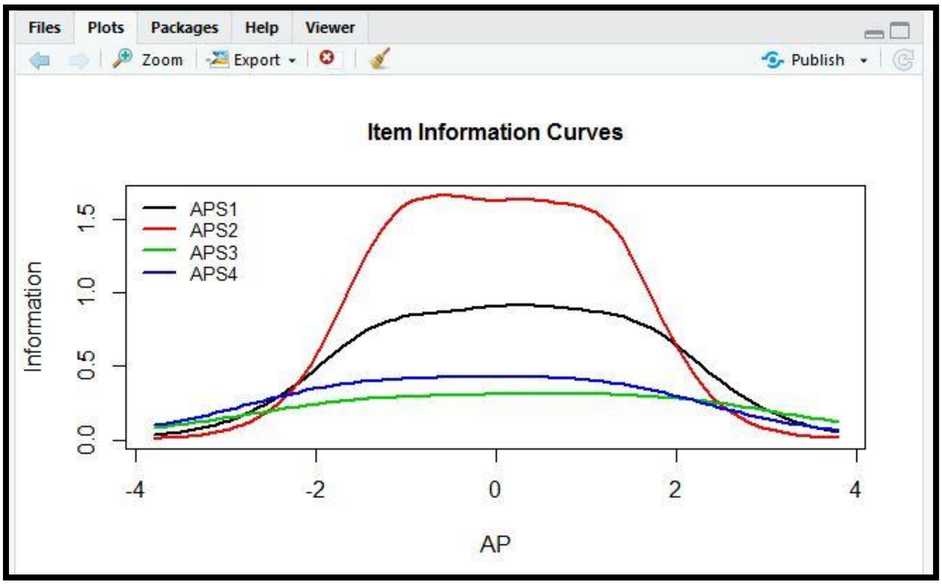


Figure 4.176 **Item Information Curve (IIC) – Academic Procrastination**

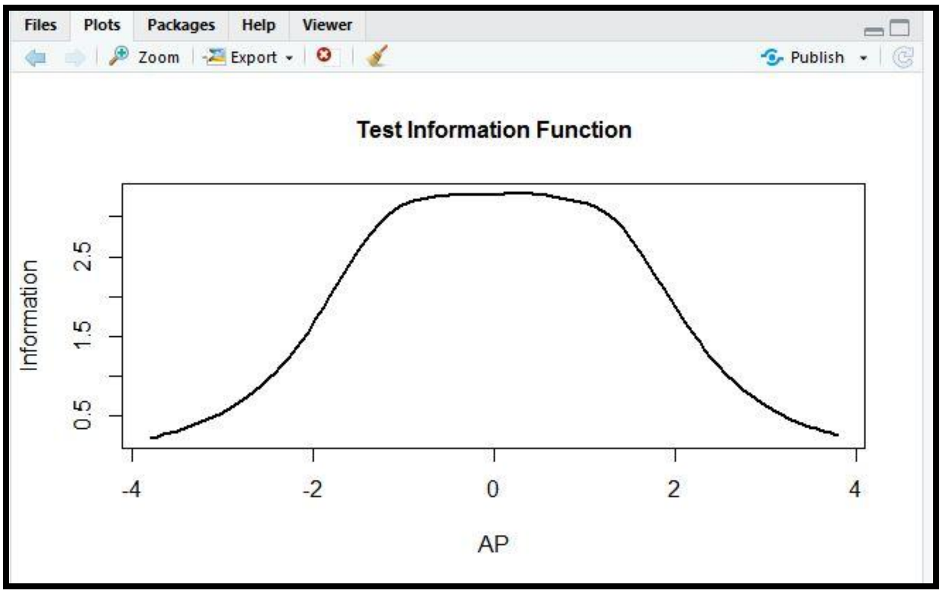


Figure 4.177 **Test Information Curve (TIC) – Academic Procrastination**

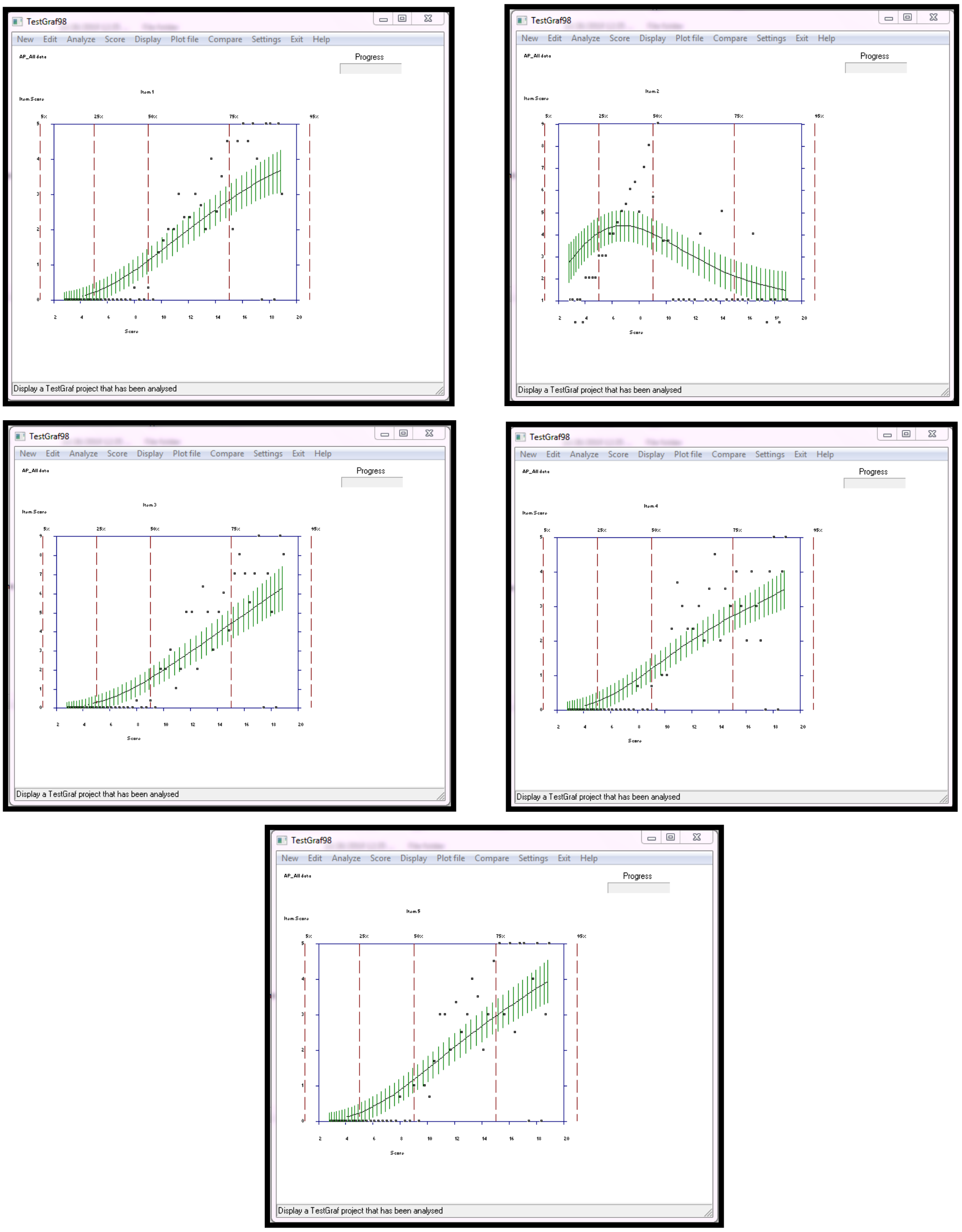


Figure 4.178 **Non-Parametric Item Characteristics Curve (ICC) for Academic Procrastination Items Using TestGraf98**

Interpretation: The item 2 of academic procrastination variable should be deleted as its ICC is not monotonous in nature.

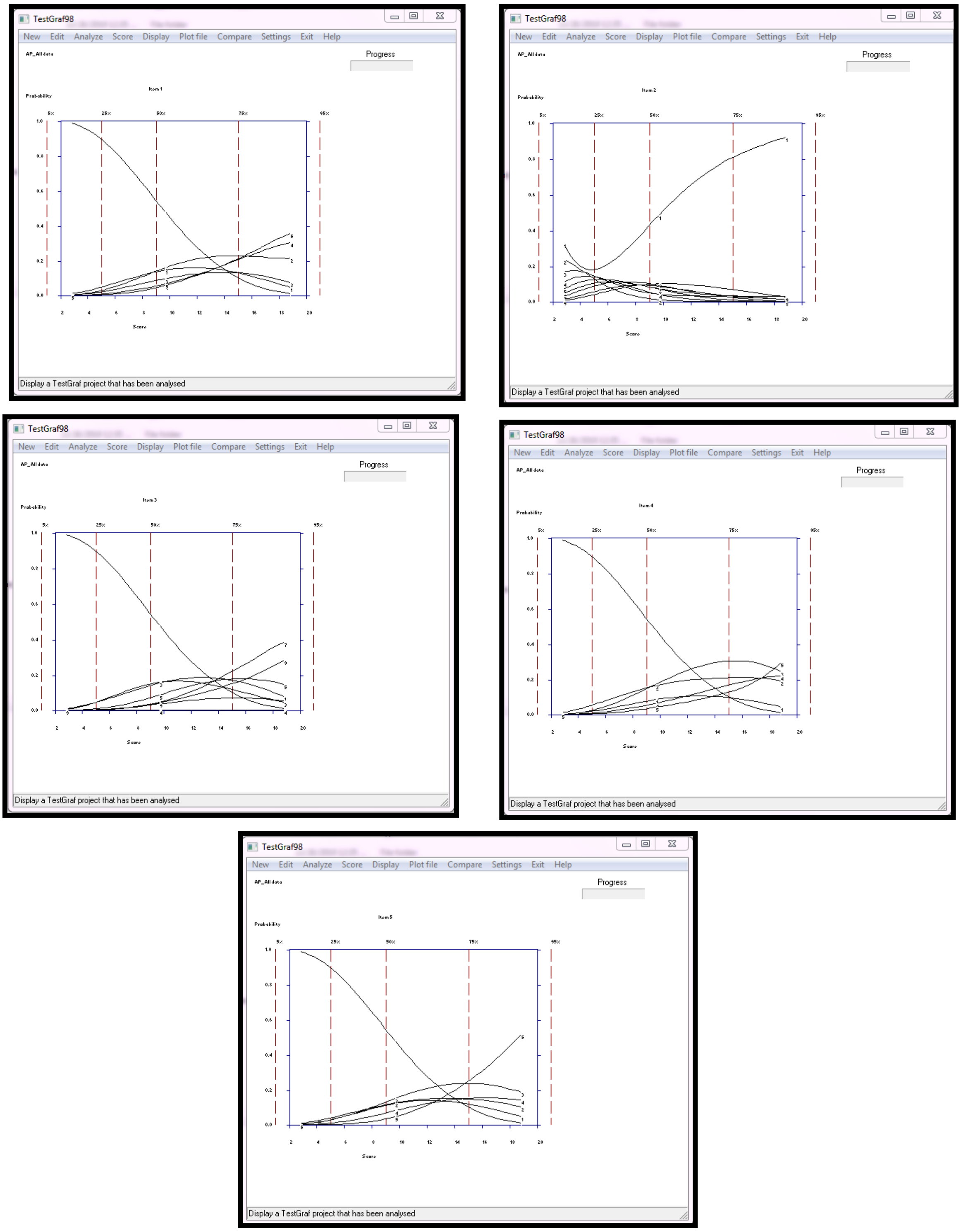


Figure 4.179 **Non Parametric Option Characteristic Curves (OCC) Academic Procrastination Items using TestGraf98:**

11. Items and Options Performance of Scale Eleven – Future Time Perspective:

```
> library(haven)
> ZTP_DATA_copy <- read_sav("D:/Item Discrimination of Final Tool Items in R/ZTP_DATA_c
opy.sav")
> View(ZTP_DATA_copy)
> fit1 <- grm(ZTP_DATA, constrained = FALSE)
> fit1

Call:
grm(data = ZTP_DATA, constrained = FALSE)

Coefficients:
      Extrmt1  Extrmt2  Extrmt3  Extrmt4  Dscrmn
ZTP11   9.684    6.066    0.061   -6.656  -0.233
ZTP12  -1.662   -0.728    0.182    1.285   1.964
ZTP13  -2.425   -1.269   -0.147    1.465   1.625
ZTP14  -4.662   -2.689   -0.340    3.089   0.684

Log.Lik: -1064.806

> fit2 <- grm(ZTP_DATA_copy, constrained = FALSE)
> fit2

Call:
grm(data = ZTP_DATA_copy, constrained = FALSE)

Coefficients:
      Extrmt1  Extrmt2  Extrmt3  Extrmt4  Dscrmn
ZTP12  -1.693   -0.740    0.189    1.309   1.886
ZTP13  -2.379   -1.251   -0.146    1.439   1.683
ZTP14  -4.687   -2.702   -0.341    3.105   0.680

Log.Lik: -787.021
```

Figure 4.180– **Item Discrimination Report – Future Time Perspective**

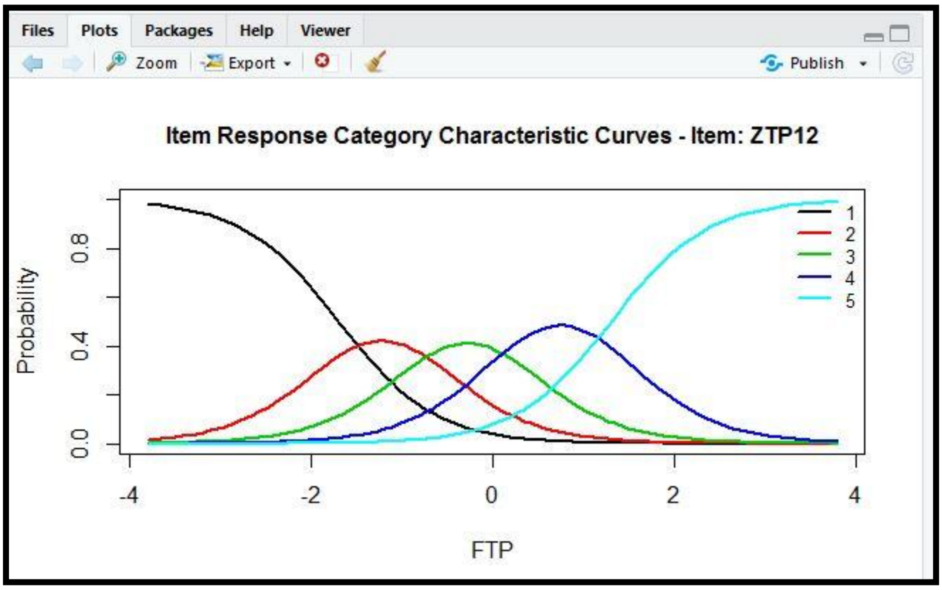


Figure 4.181– **Item Characteristic Curve (ICC) – ZTP12**

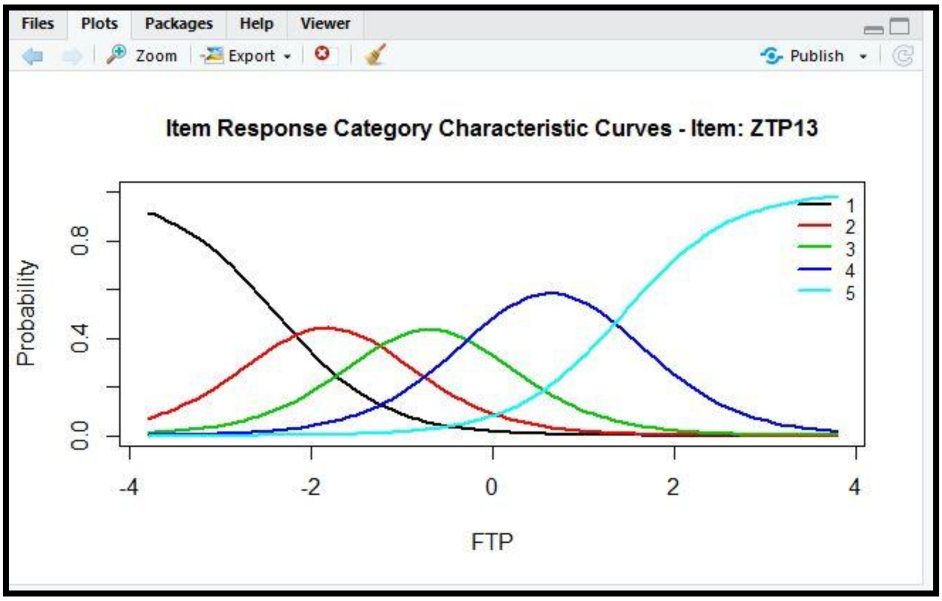


Figure 4.182– **Item Characteristic Curve (ICC) – ZTP13**

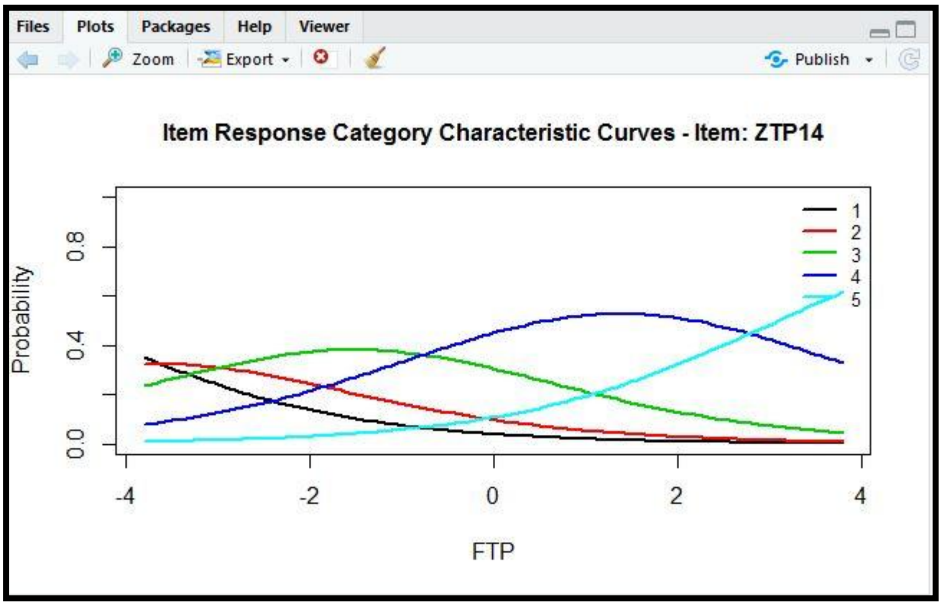


Figure 4.183– **Item Characteristic Curve (ICC) – ZTP14**

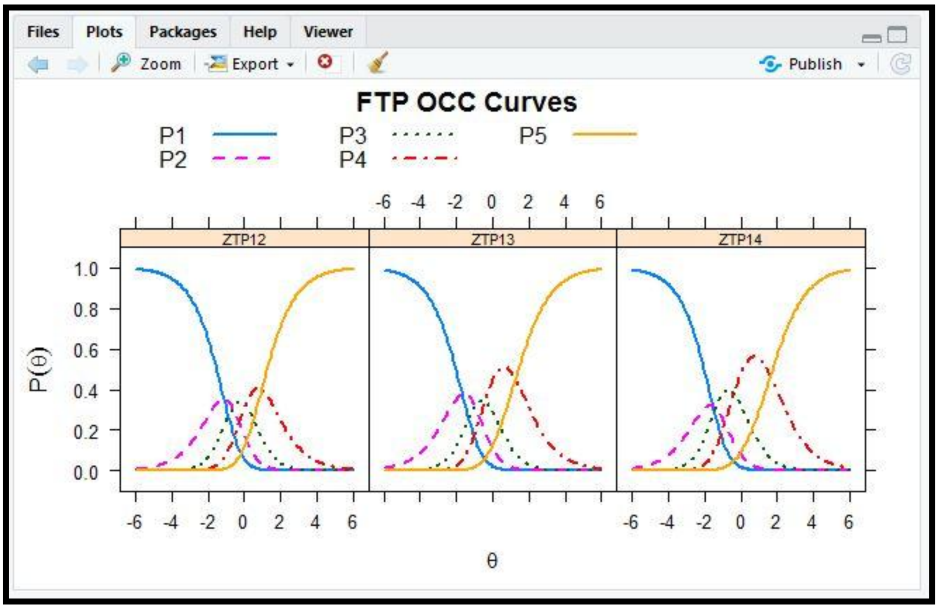


Figure 4.184– **Option Characteristic Curve (OCC) – Future Time Perspective**

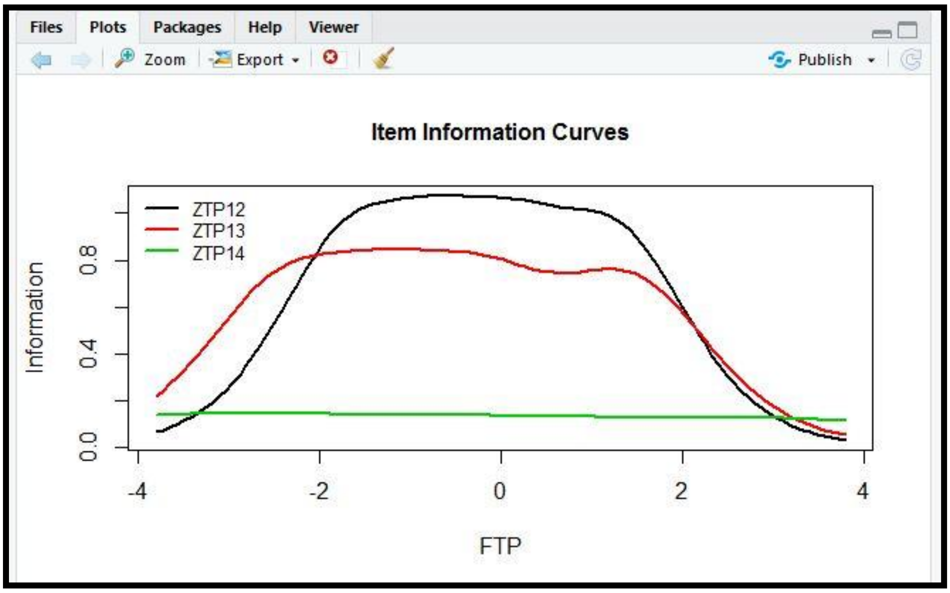


Figure 4.185– **Item Information Curve (IIC) – Future Time Perspective**

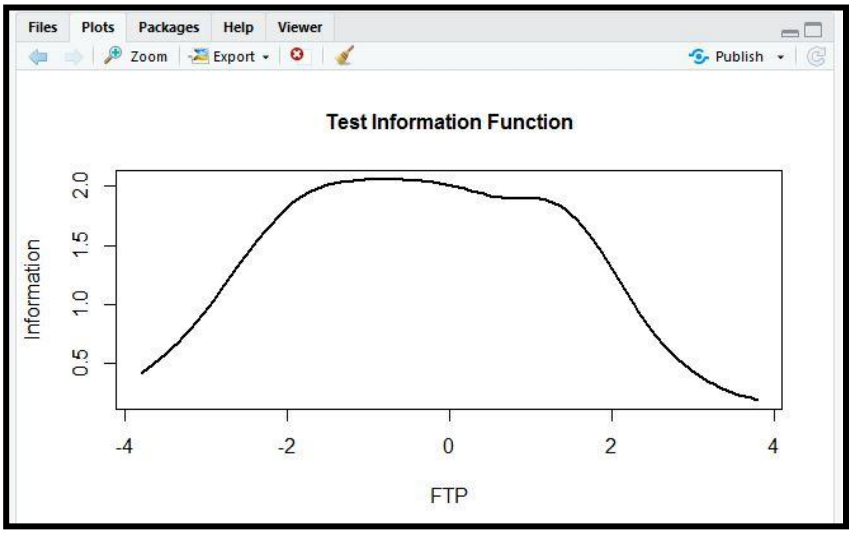


***Figure 4.186*– Test Information Curve (TIC) – Future Time Perspective**

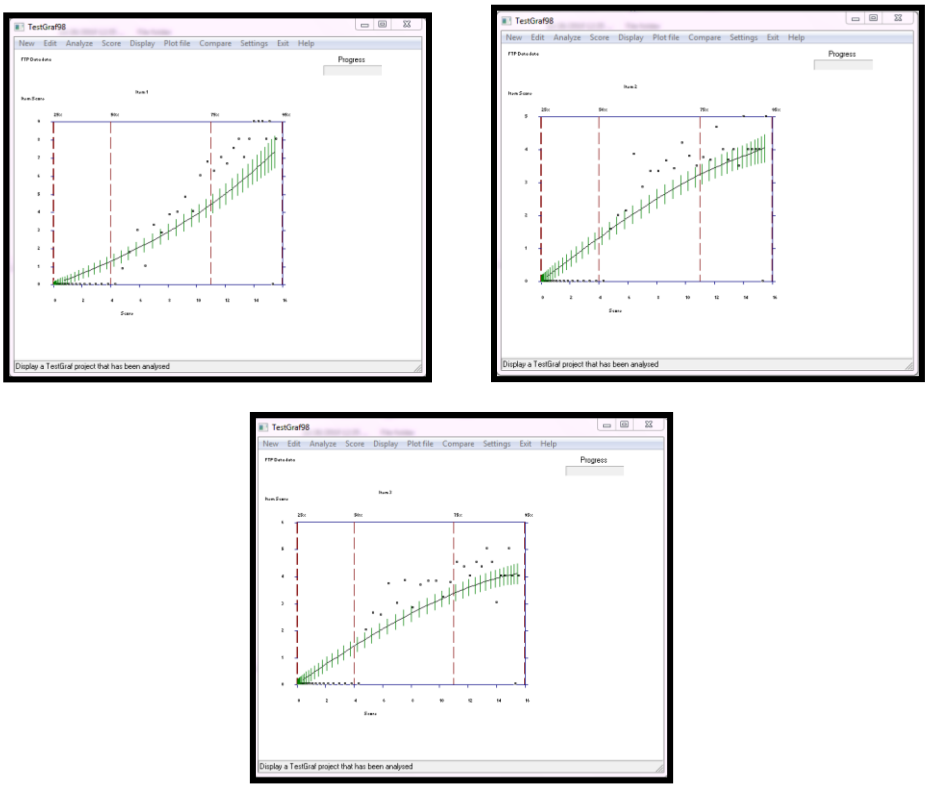


***Figure 4.187* Non-Parametric Item Characteristics Curve (ICC) for Future Time Perspective Items Using TestGraf98:**

Interpretation: The ICC curves of all the three items of future time perspective variable are fairly monotonous to be included in the scale satisfying the requirement of assumption of monotonicity of NIRT.

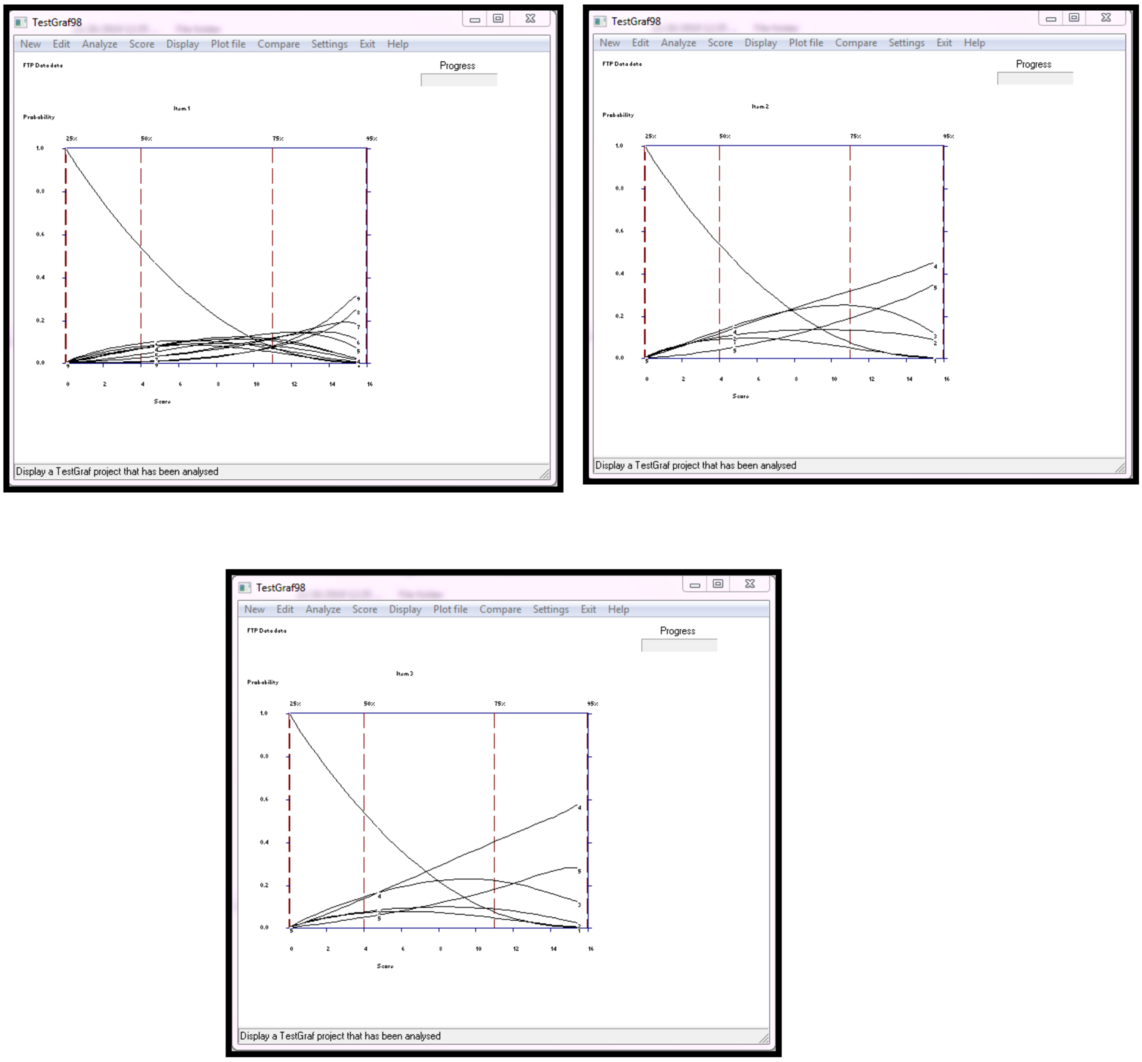


Figure 4.188 **Non Parametric Option Characteristic Curves (OCC) Future Time Perspective Items using TestGraf98**

12. Items and Options Performance of Scale Twelve – Time and Study Environment:

```
Coefficients:
     Extrmt1  Extrmt2  Extrmt3  Extrmt4  Extrmt5  Extrmt6  Dscrmn
M35   -3.243   -2.514   -1.645   -0.731    0.203    1.146   1.320
M43   -2.740   -2.050   -1.331   -0.452    0.421    1.362   1.596
M52    3.486    1.184   -0.725   -2.582   -4.208   -5.879  -0.508
M65   -2.636   -1.920   -1.247   -0.397    0.627    1.609   1.309
M70   -2.435   -1.741   -1.069   -0.279    0.519    1.489   1.545
M73   -3.200   -2.414   -1.670   -0.722    0.245    1.027   1.282
M77    4.067    1.625   -0.650   -2.450   -4.022   -5.770  -0.479
M80    3.870    1.469   -0.484   -2.231   -3.497   -5.061  -0.481

Log.Lik: -25272.07

> fit2 <- grm(BEH_Copy, constrained = FALSE)
> fit2

Call:
grm(data = BEH_Copy, constrained = FALSE)

Coefficients:
     Extrmt1  Extrmt2  Extrmt3  Extrmt4  Extrmt5  Extrmt6  Dscrmn
M35   -3.213   -2.490   -1.632   -0.729    0.197    1.135   1.339
M43   -2.542   -1.905   -1.239   -0.419    0.395    1.270   1.849
M65   -2.720   -1.975   -1.278   -0.404    0.644    1.653   1.250
M70   -2.523   -1.794   -1.096   -0.284    0.533    1.532   1.459

Log.Lik: -12419.7
```

Figure 4.189**Item Discrimination Report – Time and Study Environment**

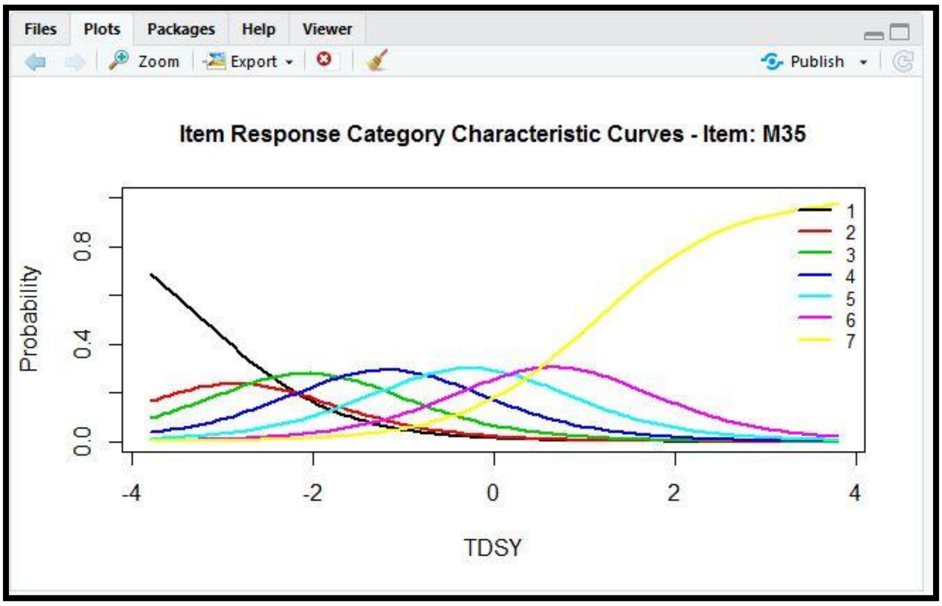


Figure 4.190**Item Characteristic Curve (ICC) – M35**

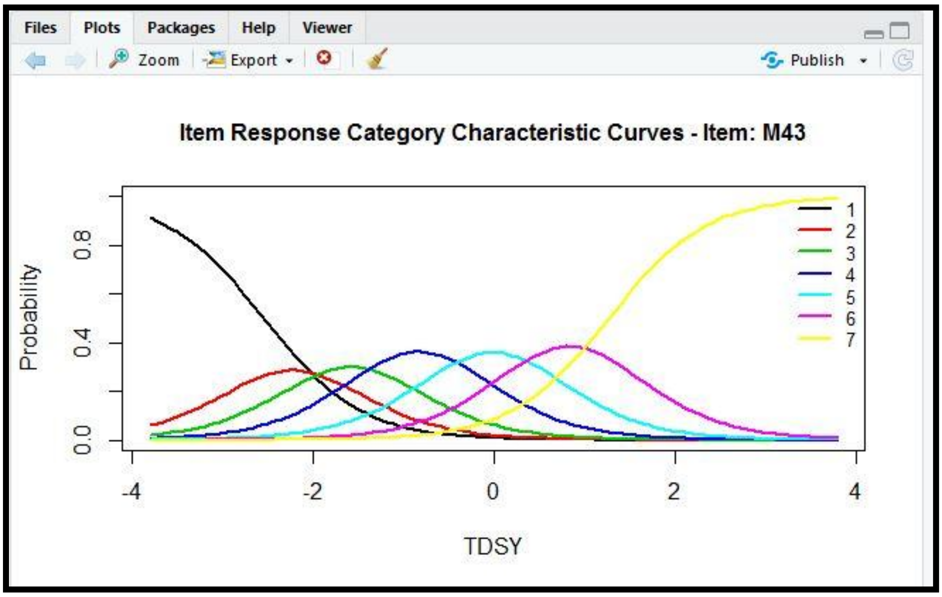


*Figure 4.191*Item Characteristic Curve (ICC) – M43

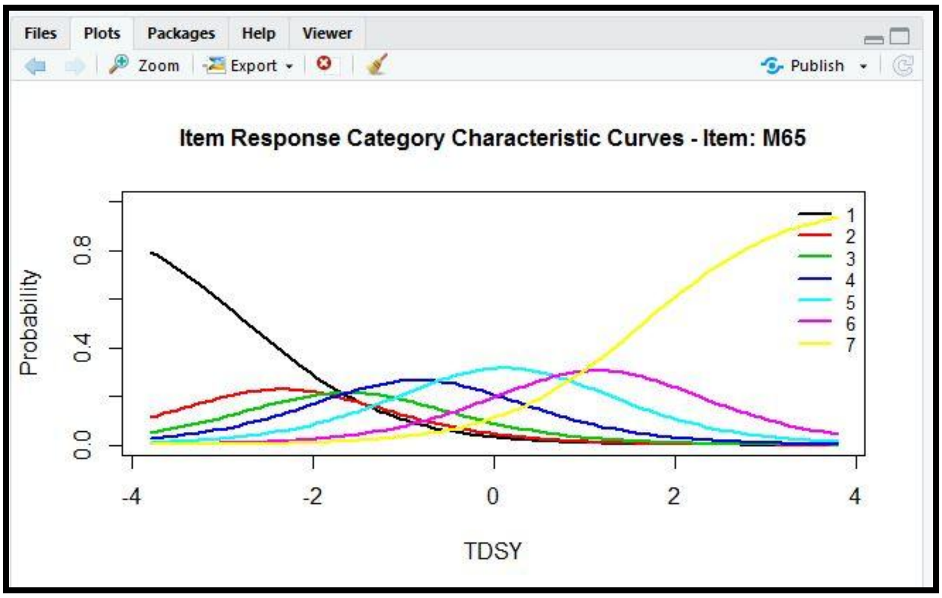


*Figure 4.192*Item Characteristic Curve (ICC) – M65

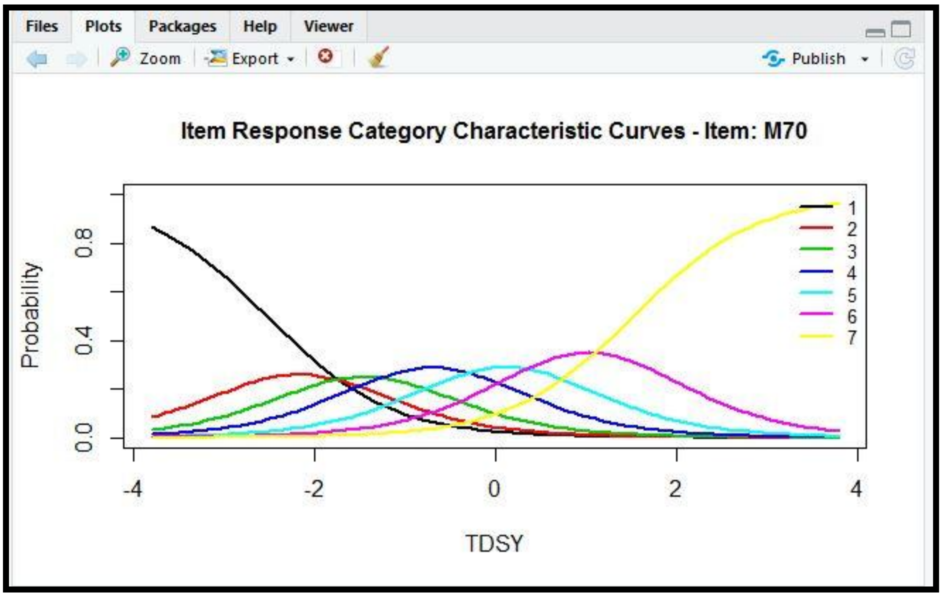


*Figure 4.193*Item Characteristic Curve (ICC) – M70

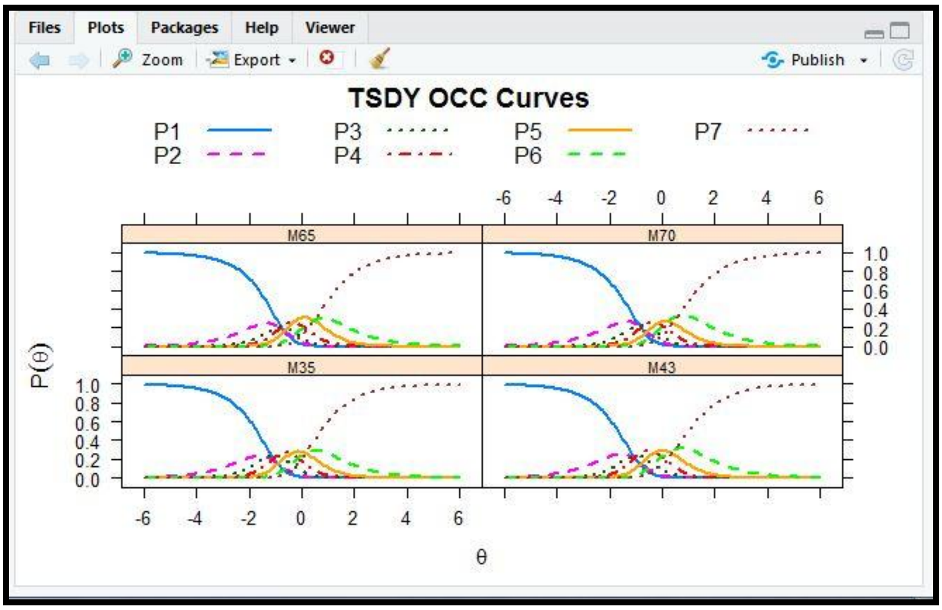


*Figure 4.194*Option Characteristic Curve (OCC) – Time and Study Environment

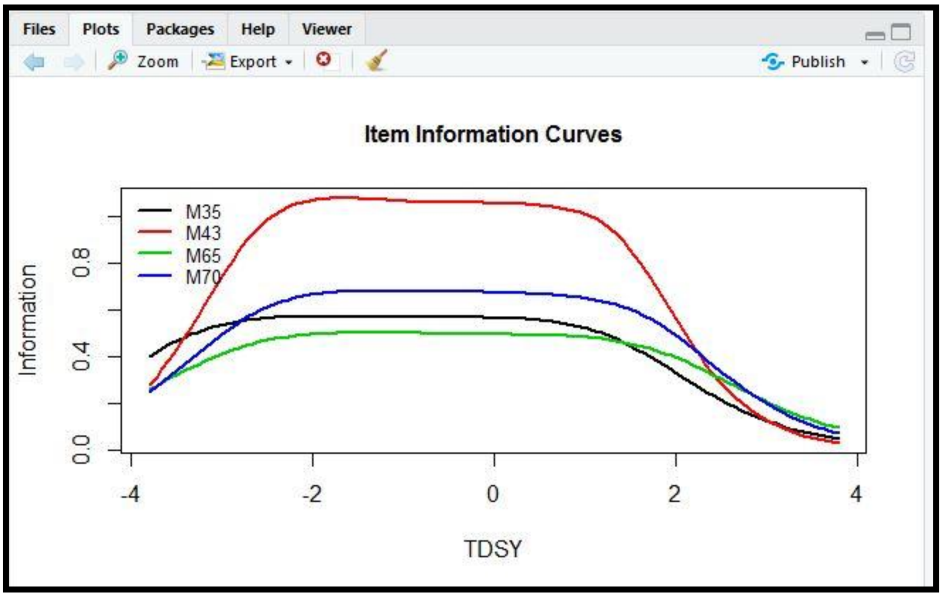


*Figure 4.195*Item Information Curve (IIC) – Time and Study Environment

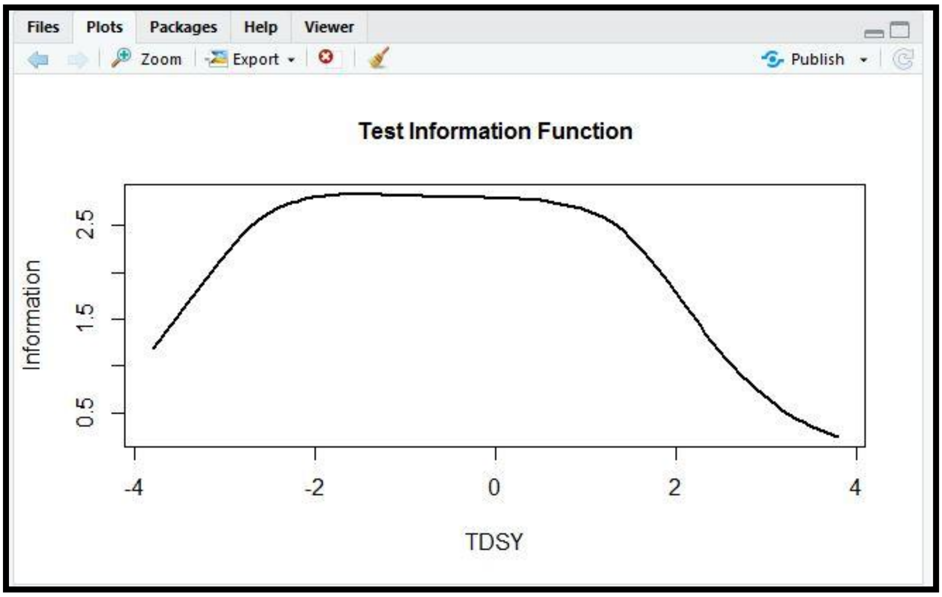
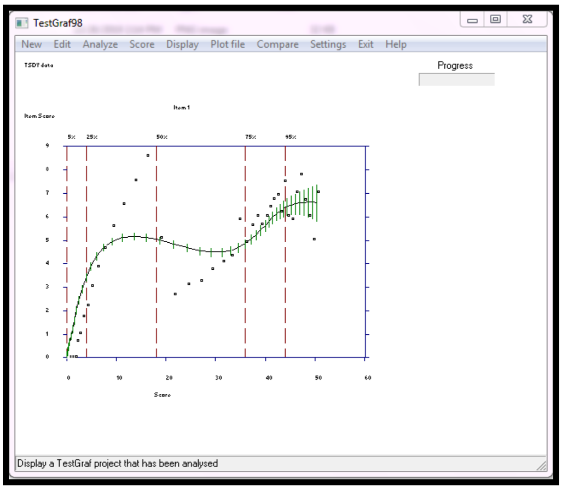
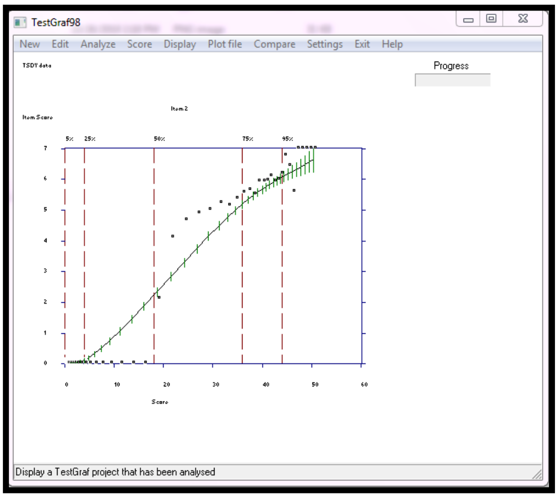
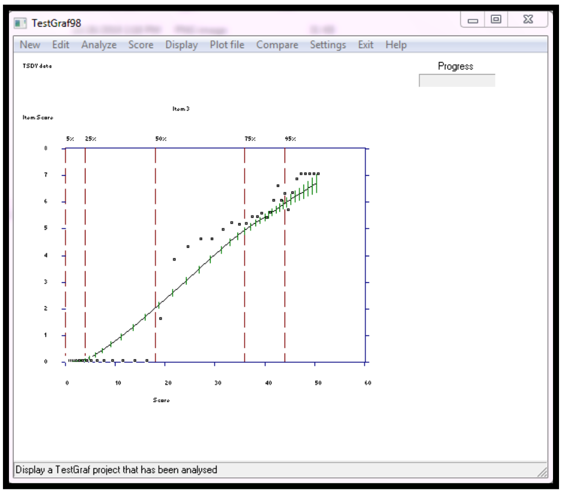
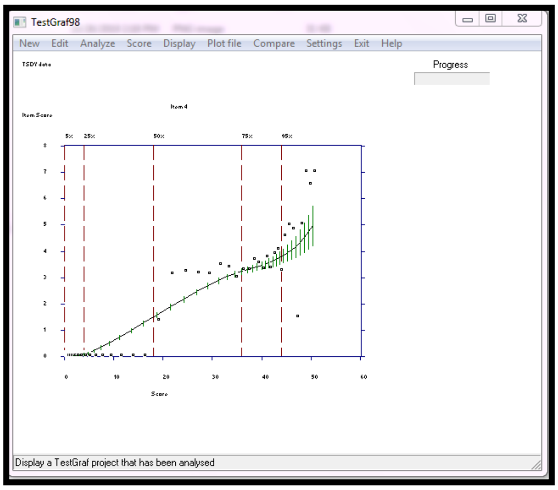


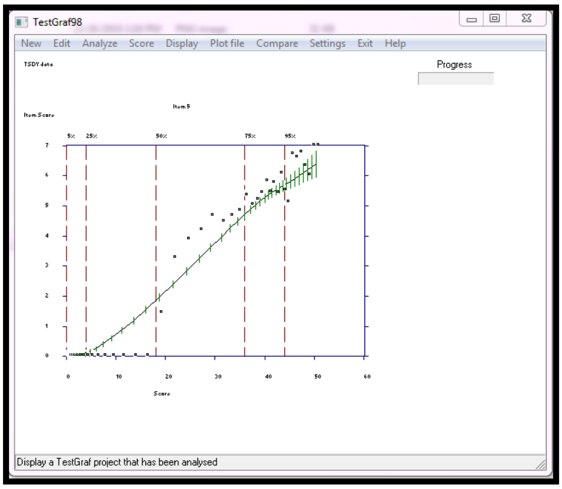
*Figure 4.196*Test Information Curve (TIC) – Time and Study Environment

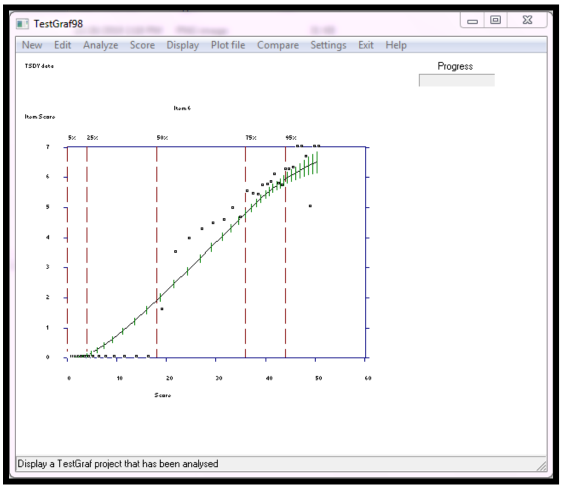

TestGraf98
New Edit Analyze Score Display Plot file Compare Settings Exit Help
Progress
Display a TestGraf project that has been analysed

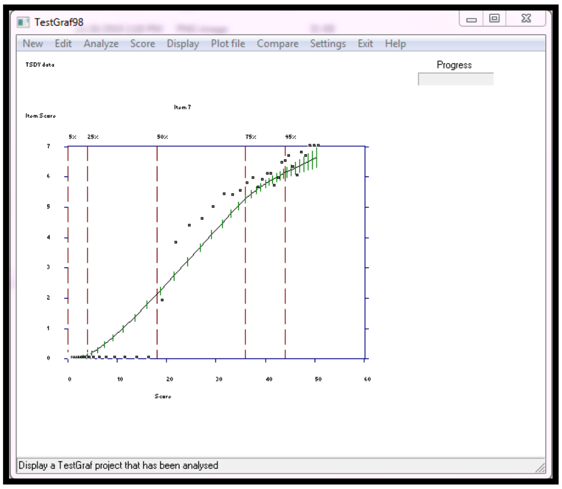

TestGraf98
New Edit Analyze Score Display Plot file Compare Settings Exit Help
Progress
Display a TestGraf project that has been analysed


TestGraf98
New Edit Analyze Score Display Plot file Compare Settings Exit Help
Progress
Display a TestGraf project that has been analysed


TestGraf98
New Edit Analyze Score Display Plot file Compare Settings Exit Help
Progress
Display a TestGraf project that has been analysed


TestGraf98
New Edit Analyze Score Display Plot file Compare Settings Exit Help
Progress
Display a TestGraf project that has been analysed





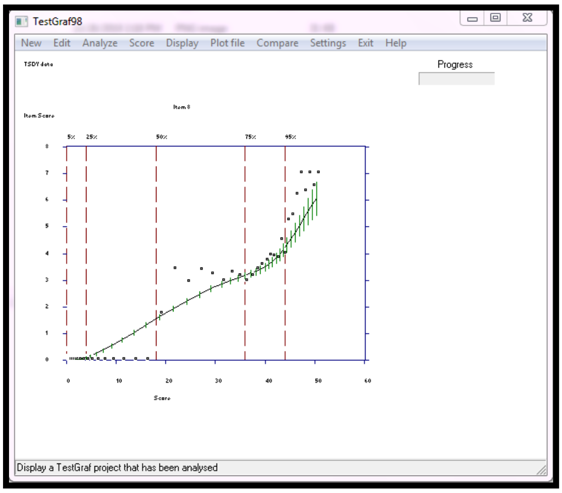
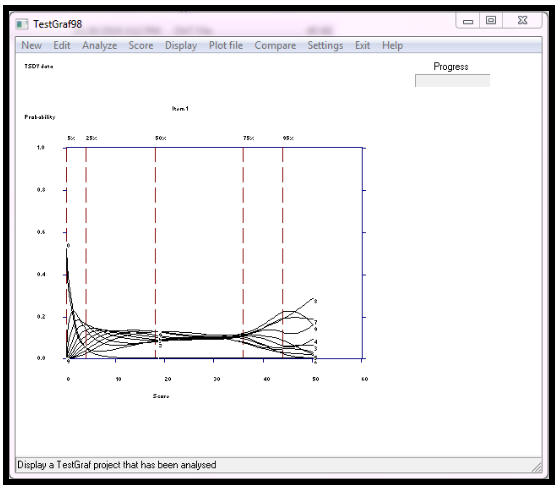
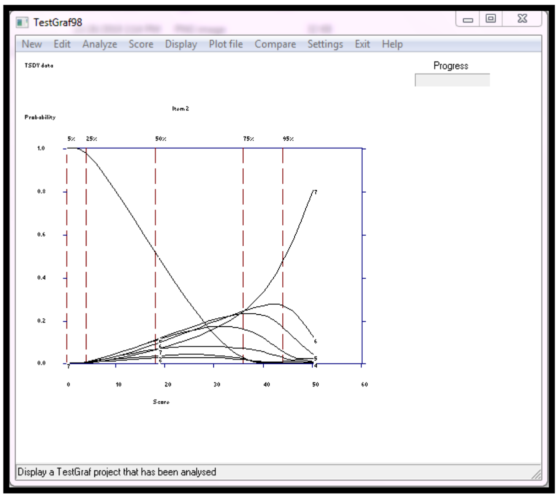
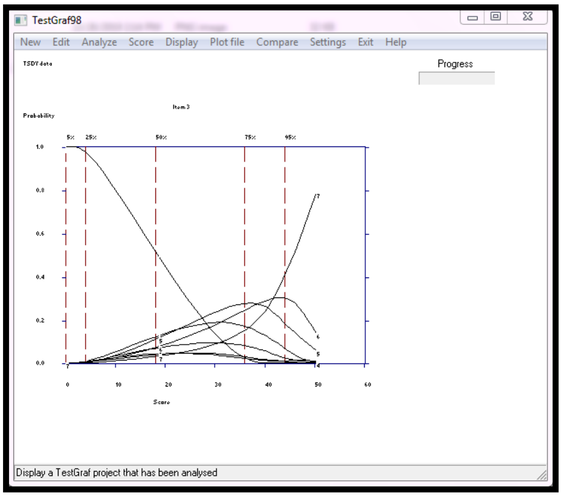


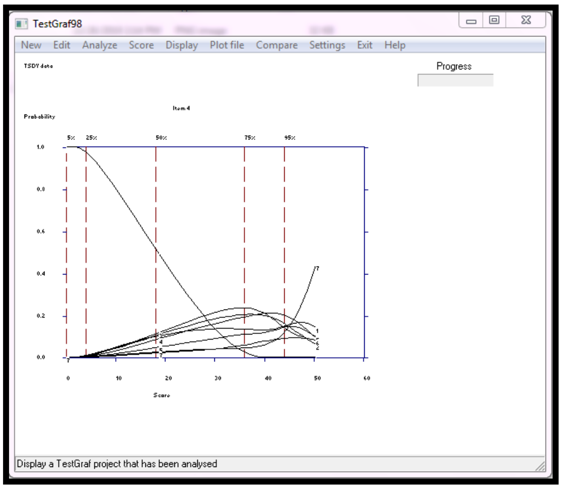
Figure 4.197 **Non-Parametric Item Characteristics Curve (ICC) for Time and Study Environment Items Using TestGraf98:**

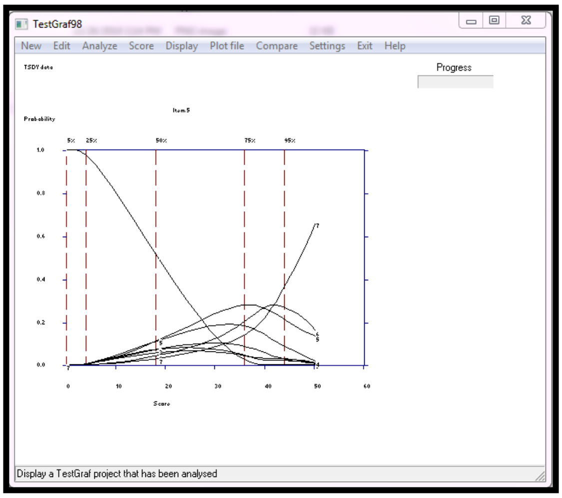
Interpretation: All the items of the variable time and study environment have monotonous item characteristic curves, except item 1.


TestGraf98
New Edit Analyze Score Display Plot file Compare Settings Exit Help
Progress
TSDY data
Item 1
Probability
5% 25% 50% 75% 95%
Score
Display a TestGraf project that has been analysed


TestGraf98
New Edit Analyze Score Display Plot file Compare Settings Exit Help
Progress
TSDY data
Item 2
Probability
5% 25% 50% 75% 95%
Score
Display a TestGraf project that has been analysed


TestGraf98
New Edit Analyze Score Display Plot file Compare Settings Exit Help
Progress
TSDY data
Item 3
Probability
5% 25% 50% 75% 95%
Score
Display a TestGraf project that has been analysed


TestGraf98
New Edit Analyze Score Display Plot file Compare Settings Exit Help
Progress
TSDY data
Item 4
Probability
5% 25% 50% 75% 95%
Score
Display a TestGraf project that has been analysed


TestGraf98
New Edit Analyze Score Display Plot file Compare Settings Exit Help
Progress
TSDY data
Item 5
Probability
5% 25% 50% 75% 95%
Score
Display a TestGraf project that has been analysed

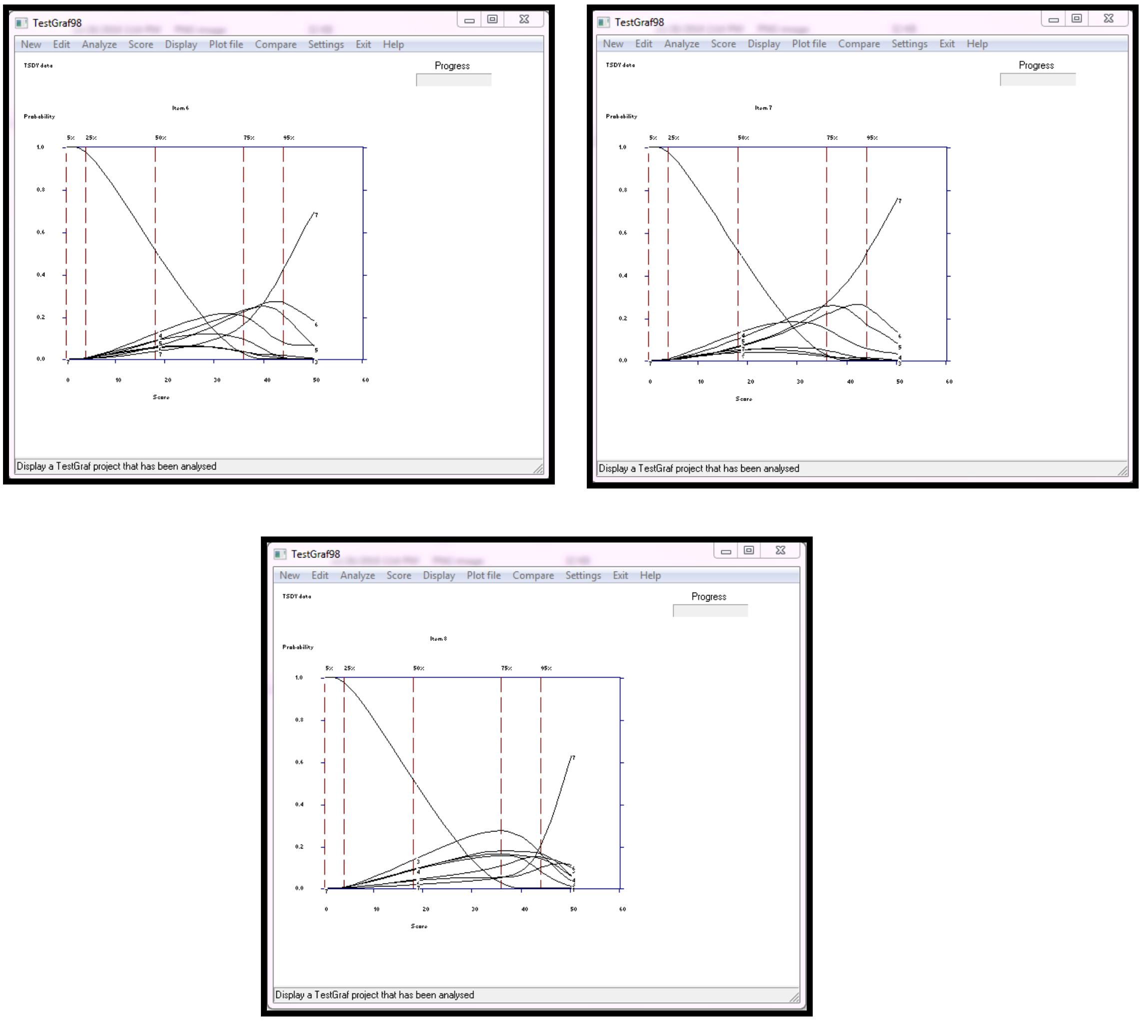


Figure 4.198 **Non Parametric Option Characteristic Curves (OCC) Time and Study Environment Items using TestGraf98:**

13. Items and Options Performance of Scale Thirteen - Reappraisal:

```
> fit1 <- grm(Reappraisal, constrained = FALSE)
> fit1

Call:
grm(data = Reappraisal, constrained = FALSE)

Coefficients:
        Extrmt1  Extrmt2  Extrmt3  Extrmt4  Dscrmn
Reapp1   -1.979   -1.082   -0.230    1.206   1.257
Reapp2   -1.697   -0.712    0.017    1.430   1.715
Reapp3   -1.898   -0.944   -0.275    0.913   2.407
Reapp4   -2.502   -1.447   -0.529    0.654   1.674
Reapp5   -1.914   -0.586    0.322    1.596   1.441

Log.Lik: -3470.727

> 
```

Figure 4.199 **Item Discrimination Report - Reappraisal**

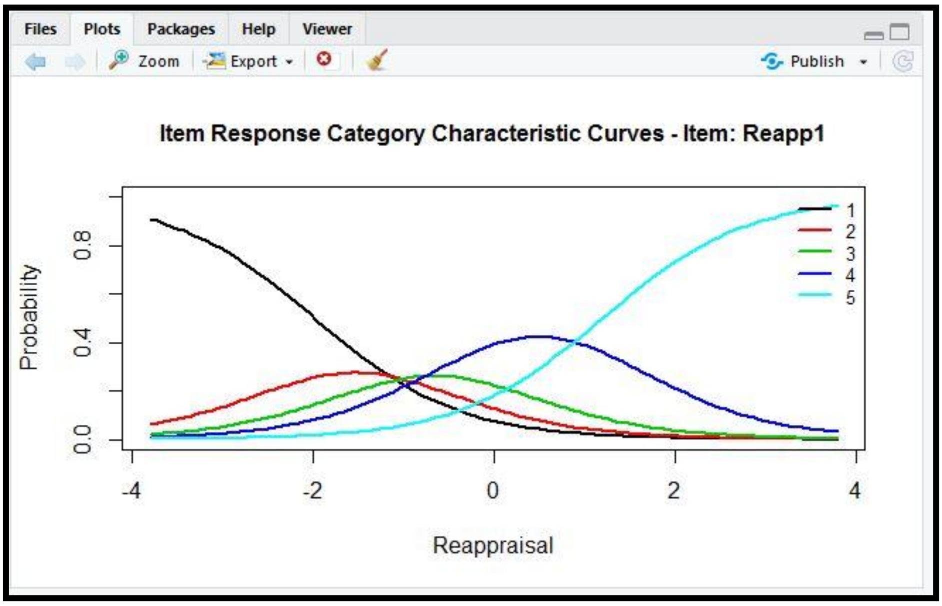


Figure 4.200 **Item Characteristic Curve (ICC) – Reapp1**

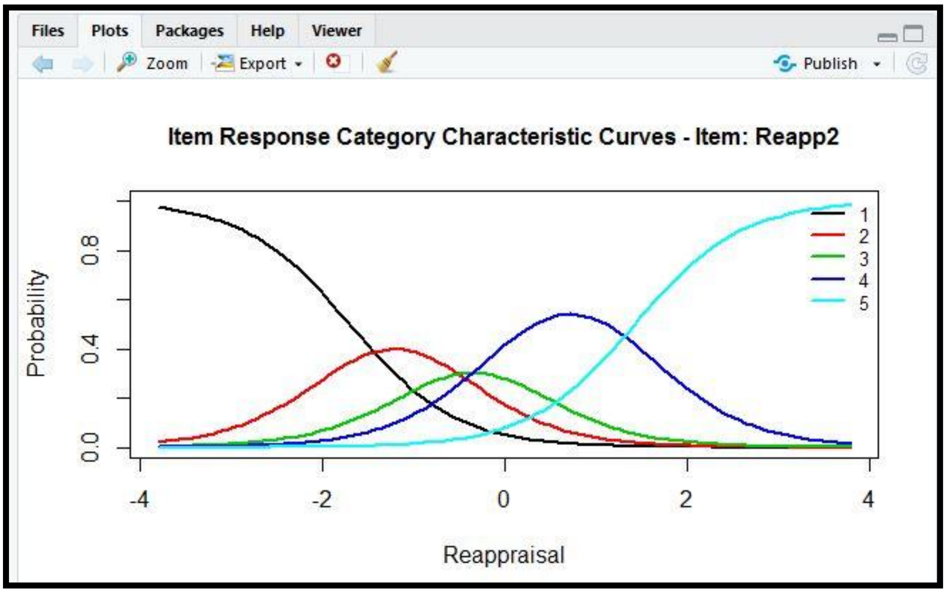


Figure 4.201 **Item Characteristic Curve (ICC) – Reapp2**

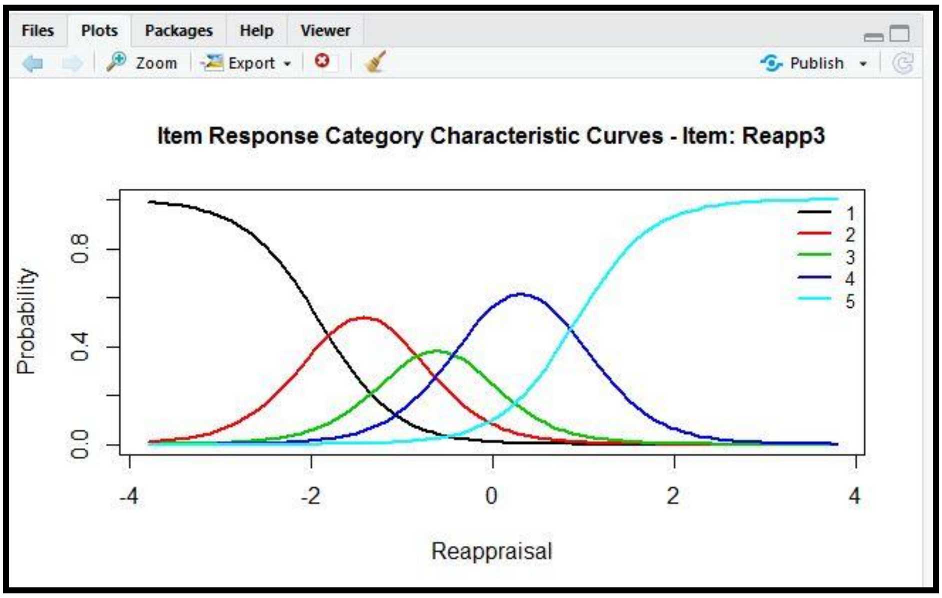


Figure 4.202 **Item Characteristic Curve (ICC) – Reapp3**

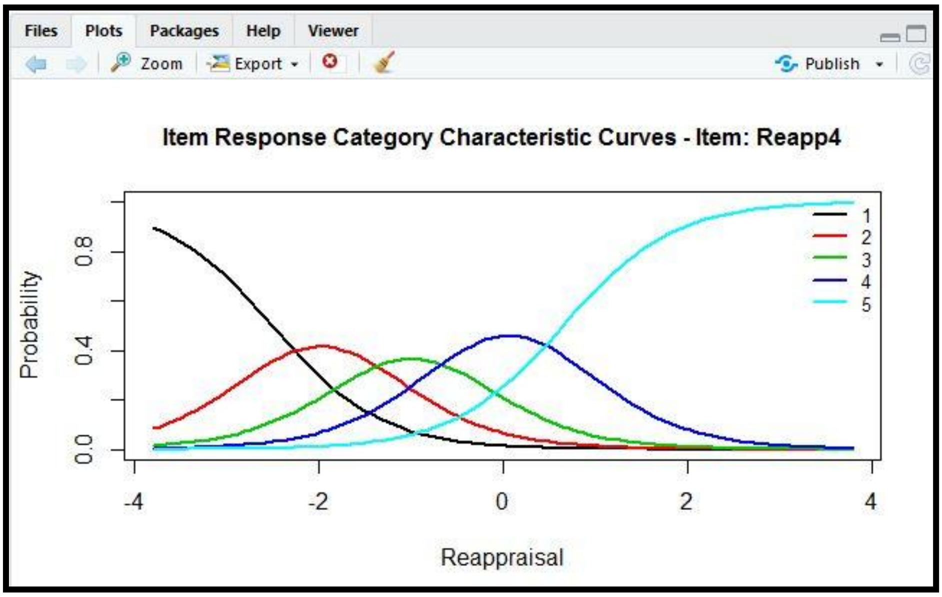


Figure 4.203 **Item Characteristic Curve (ICC) – Reapp4**

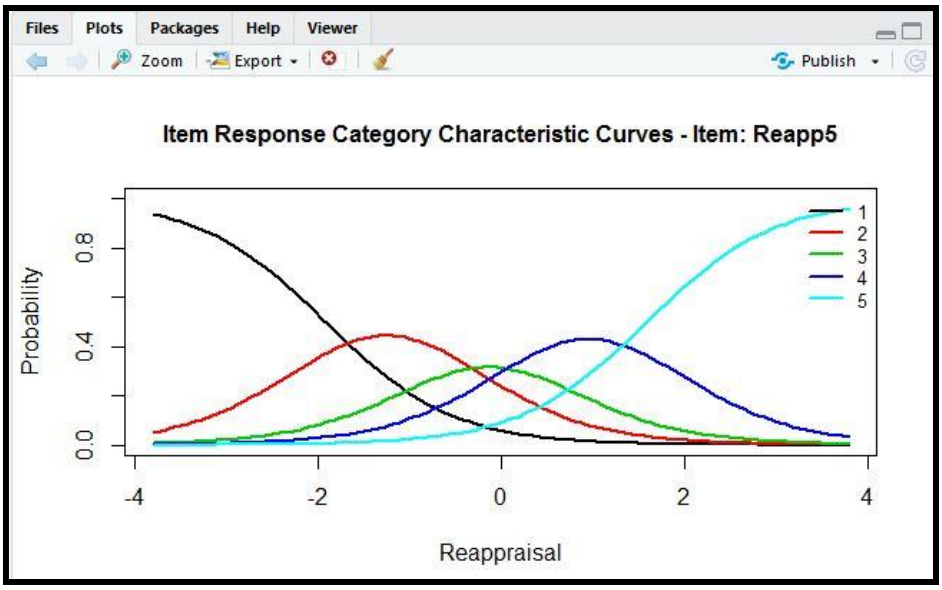


Figure 4.204 **Item Characteristic Curve (ICC) – Reapp5**

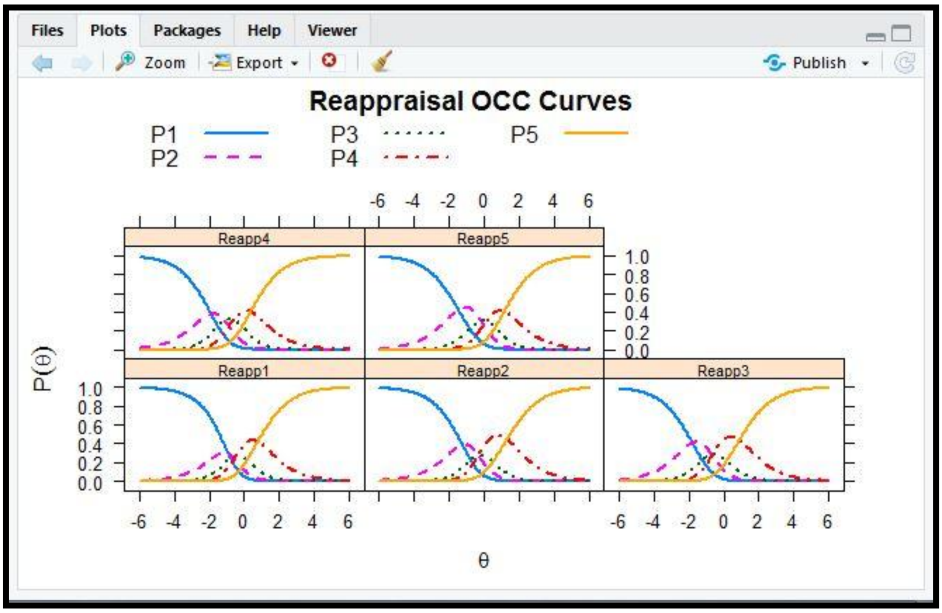


Figure 4.205 **Option Characteristic Curve (OCC) – Reappraisal**

Item Information Curve (IIC):

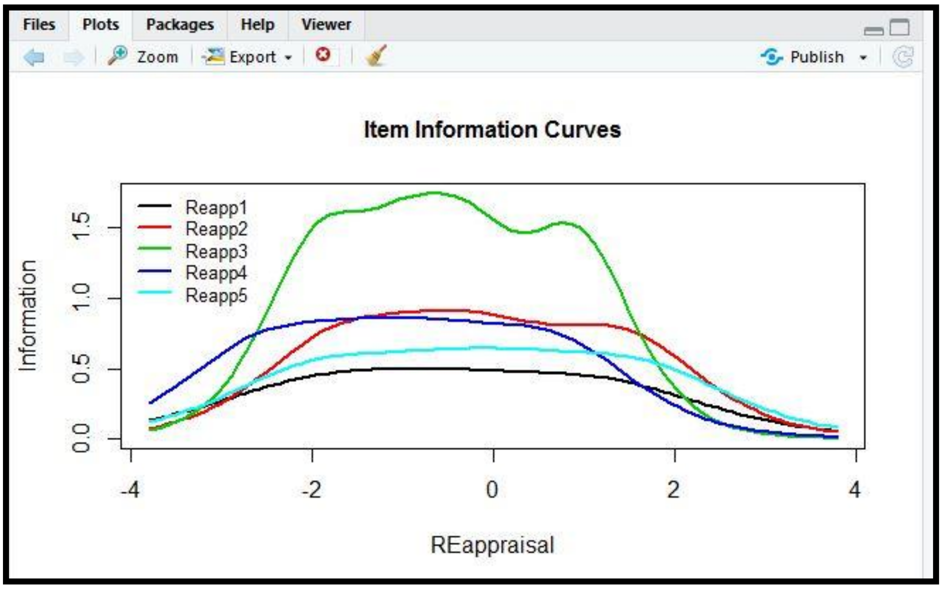


Figure 4.206 **Item Information Curve (ICC) – Reappraisal**

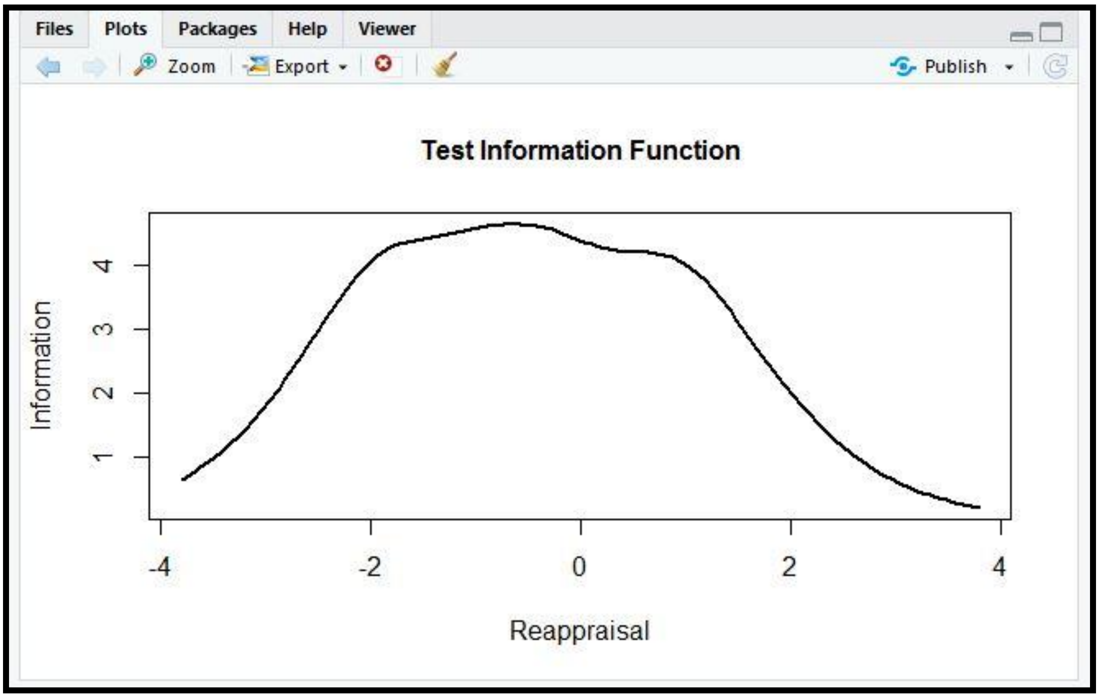
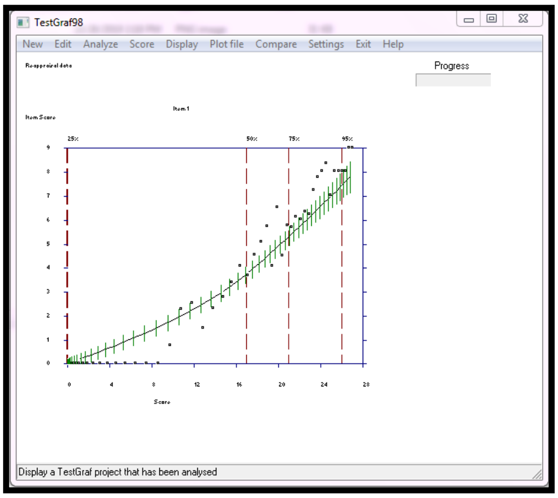
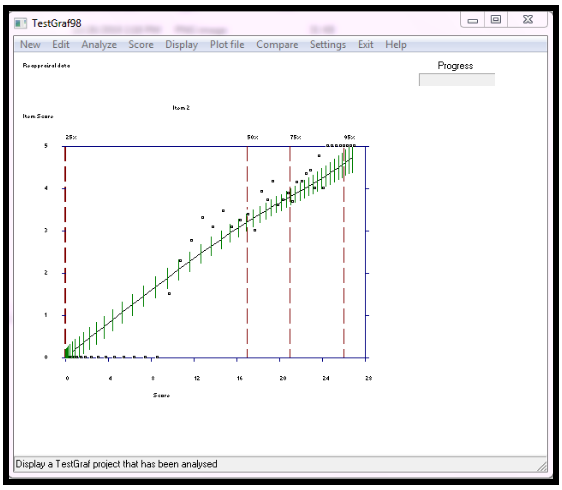


Figure 4.207 **Item Information Curve (ICC) – Reappraisal**





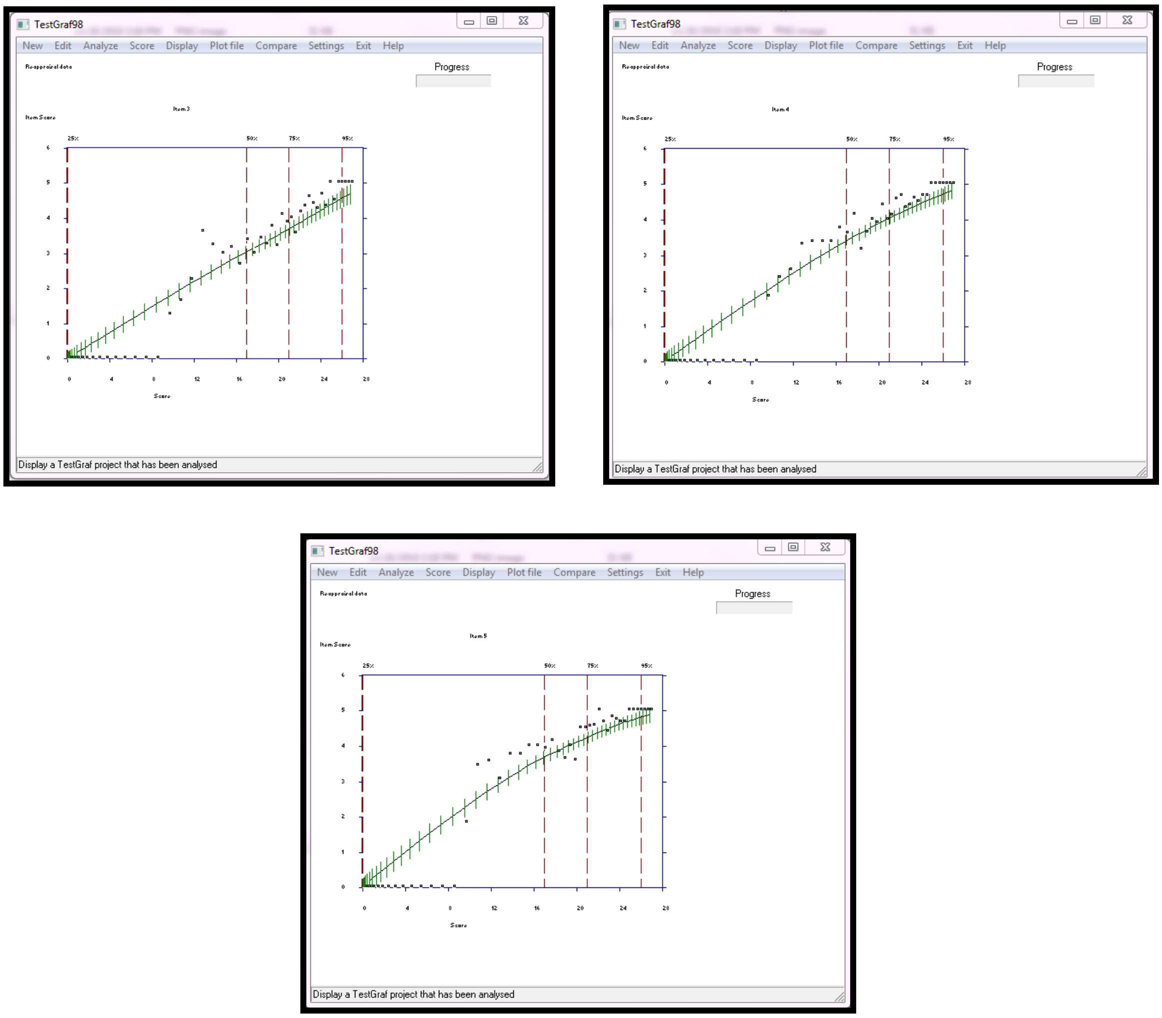


Figure 4.208 **Non-Parametric Item Characteristics Curve (ICC) for Reappraisal Items Using TestGraf98:**

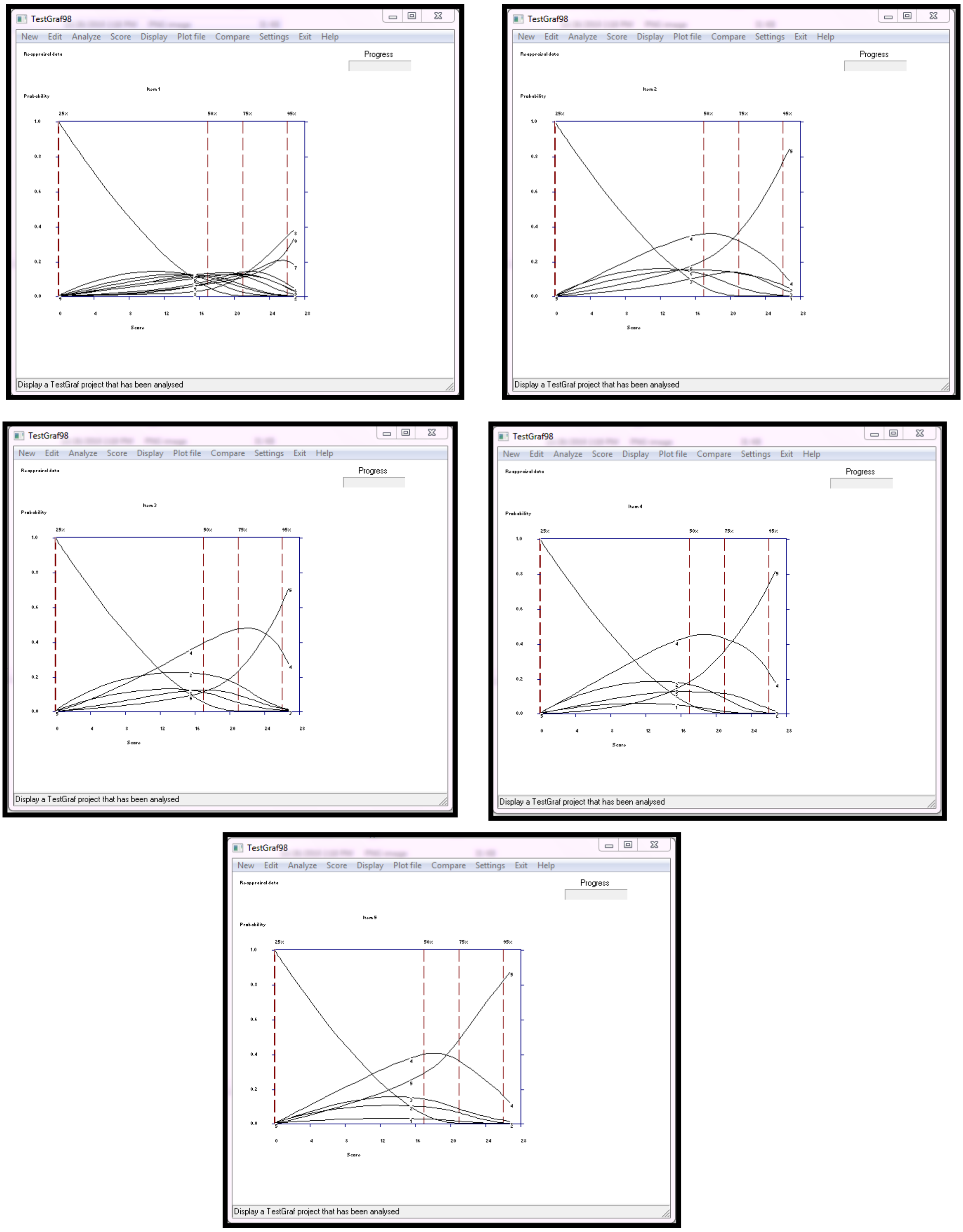


Figure 4.209 **Non Parametric Option Characteristic Curves (OCC) Reappraisal Items using TestGraf98:**

14. Items and Options Performance of Scale Fourteen – Supression:

```
> fit1 <- grm(Suppression, constrained = FALSE)
> fit1

Call:
grm(data = Suppression, constrained = FALSE)

Coefficients:
       Extrmt1  Extrmt2  Extrmt3  Extrmt4  Dscrmn
Supp1   -2.906   -1.402    0.073    1.811   1.238
Supp2   -2.641   -1.562   -0.303    1.480   1.288
Supp3   -2.794   -1.922   -0.461    1.195   1.443
Supp4   -2.214   -1.266   -0.199    1.354   1.548
Supp5   -2.344   -1.256   -0.241    1.342   1.484

Log.Lik: -3379.571
```

Figure 4.210 **Item Discrimination Report – Suppression**

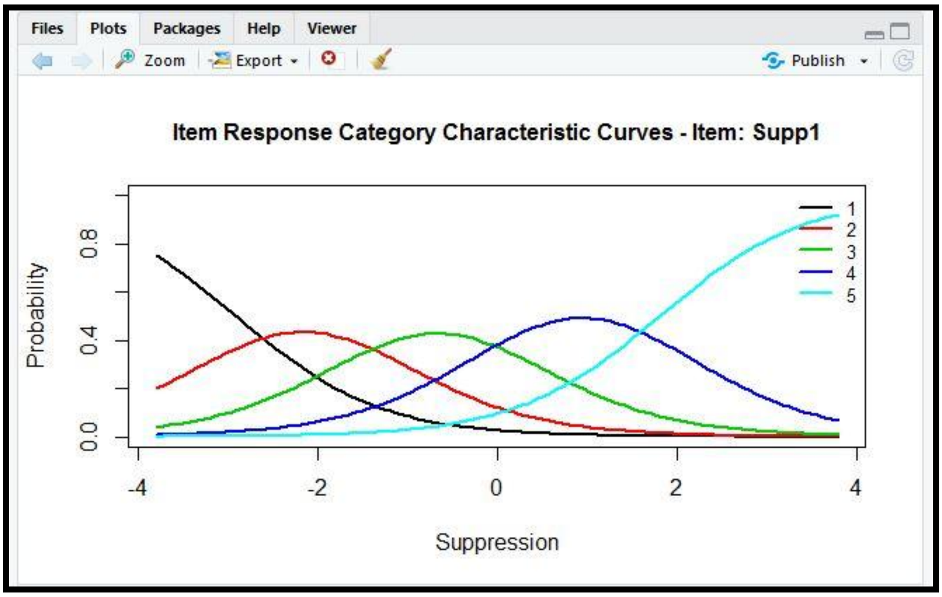


***Figure 4.211 Item Characteristic Curves* (ICC) – Supp1**

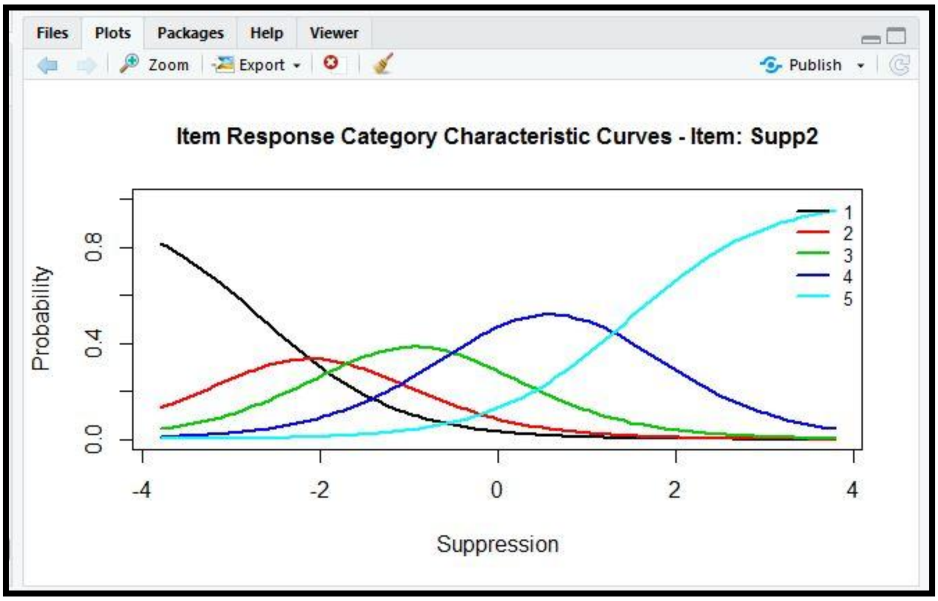


Figure 4.212 Item Characteristic Curves (ICC) – Supp2

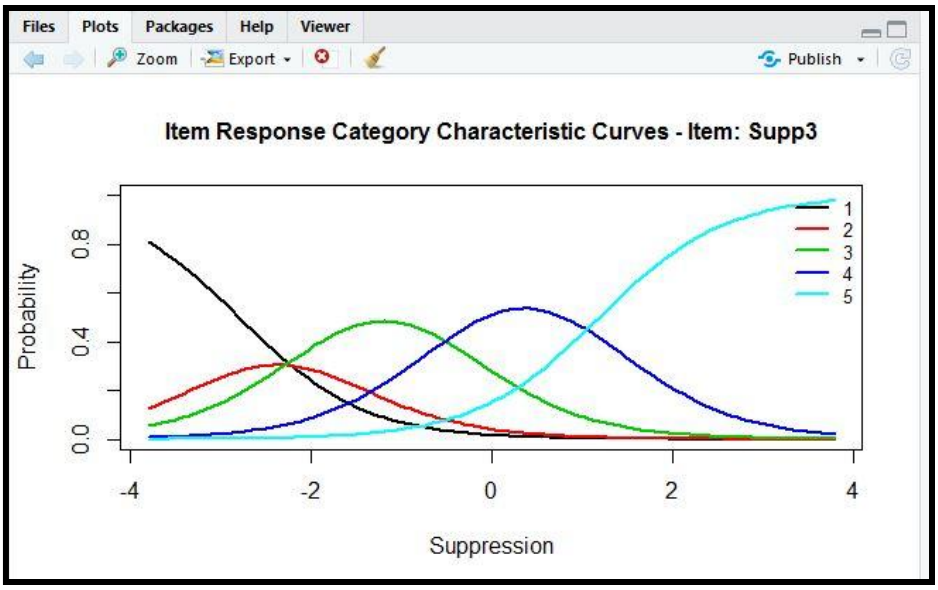


Figure 4.213 Item Characteristic Curves (ICC) – Supp3

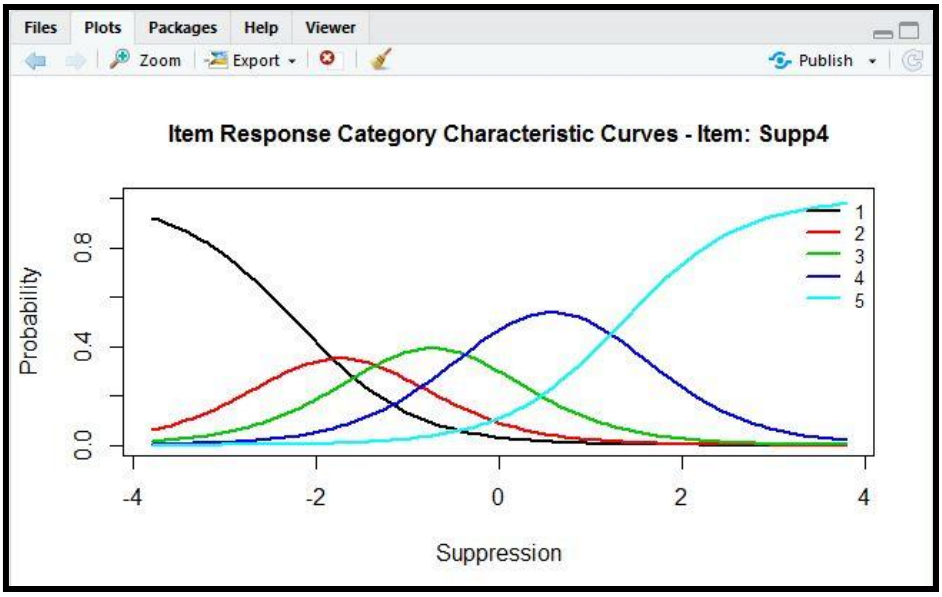


Figure 4.214 **Item Characteristic Curve (ICC) – Supp4**

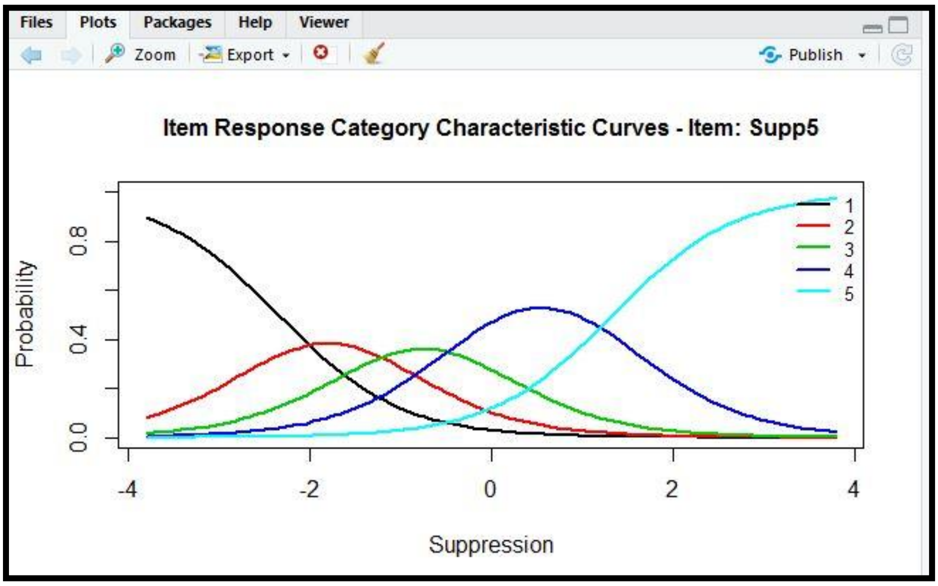


***Figure 4.215 Item Characteristic Curves* (ICC) – Supp5**

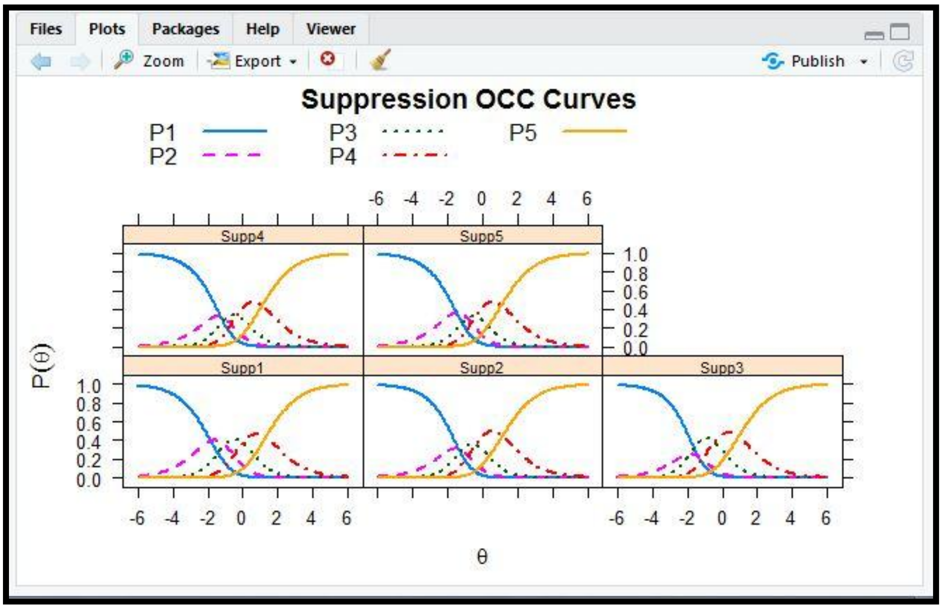


Figure 4.216 Option Characteristic Curves **(OCC) – Suppression**

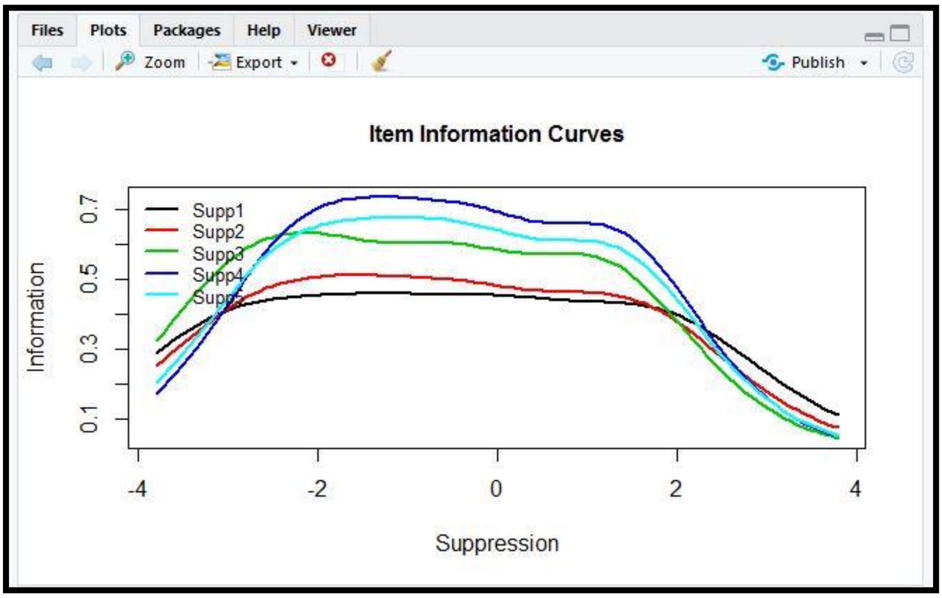


Figure 4.217 **Item Information Curve (IIC) – Suppression**

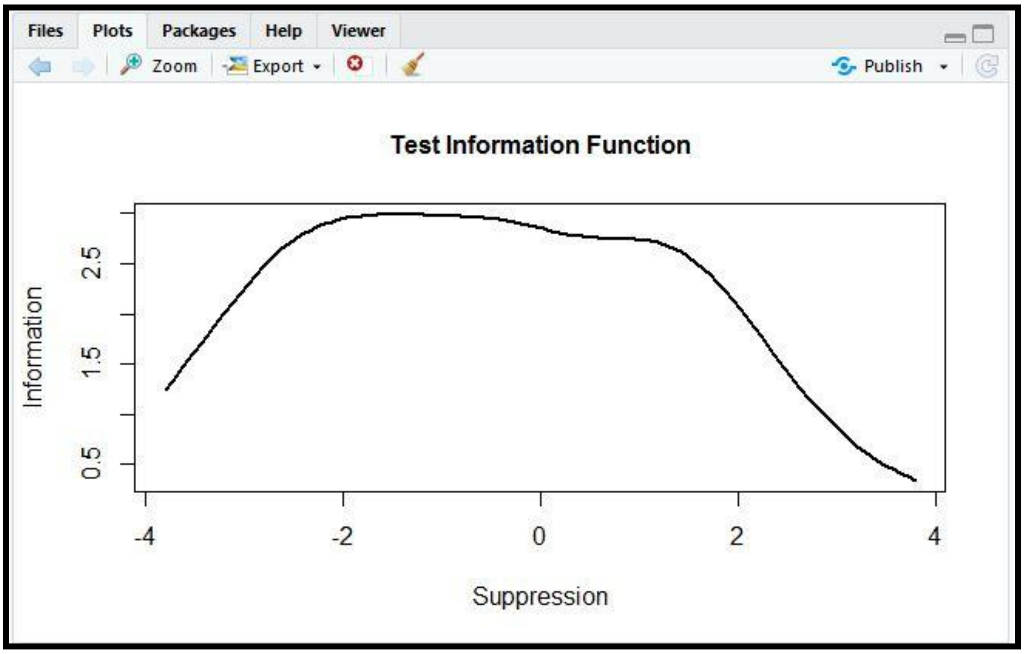
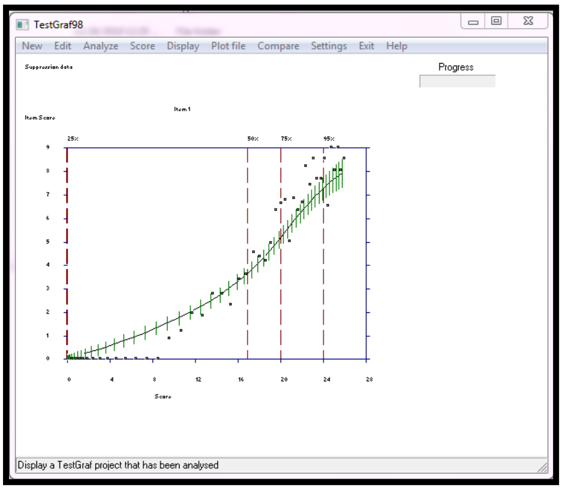
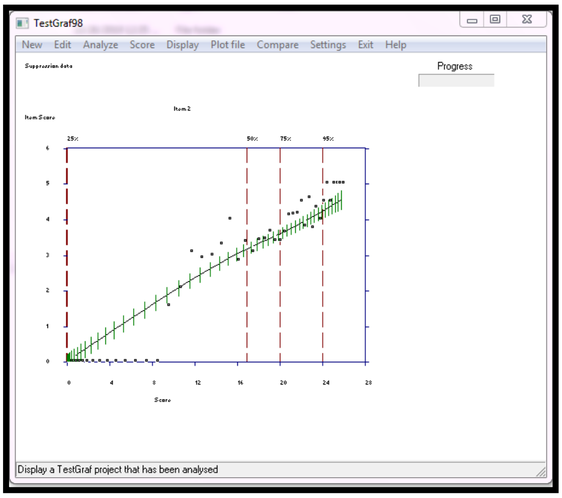


Figure 4.218 **Test Information Curve (TIC) – Suppression**





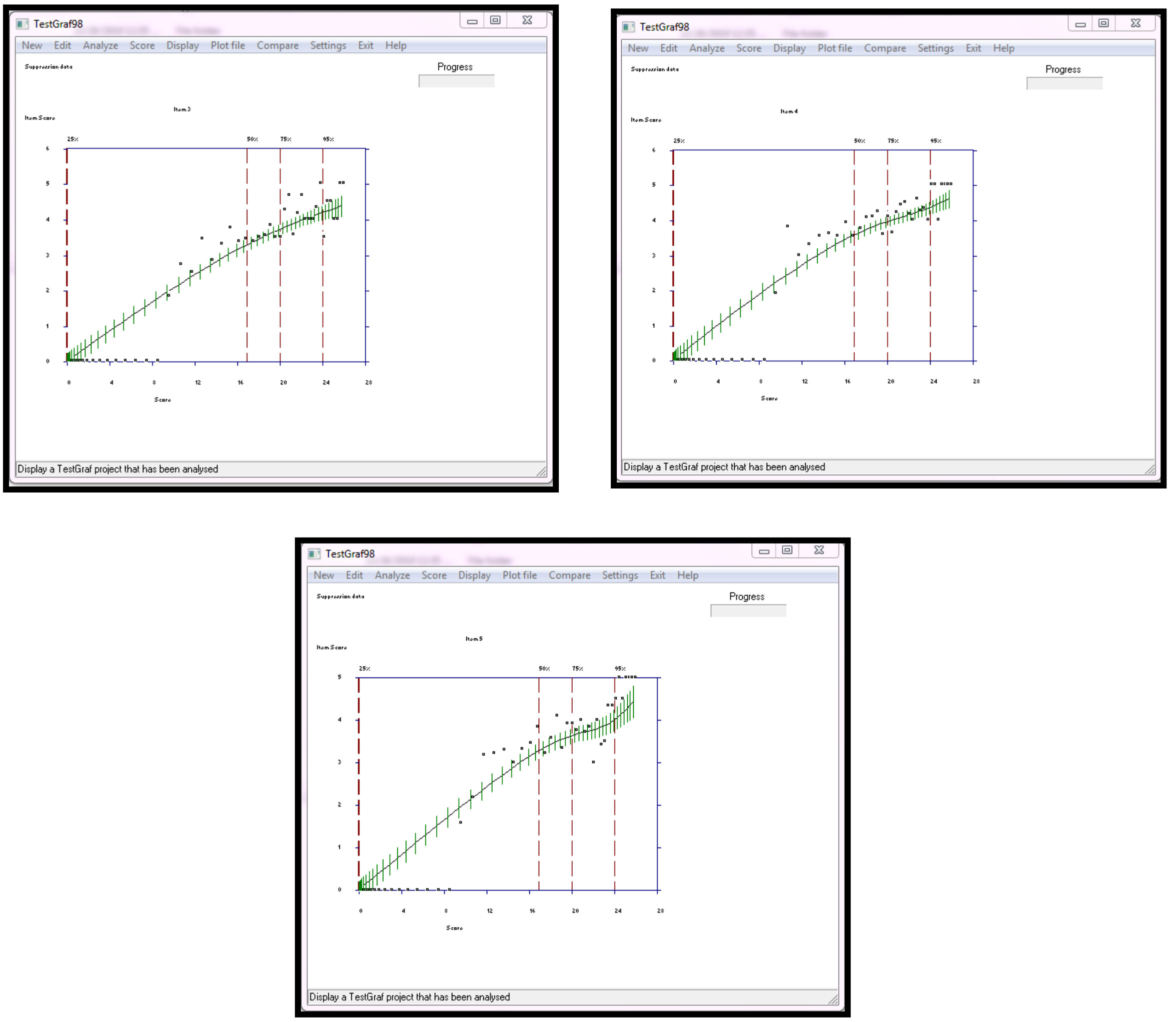


Figure 4.219 **Non-Parametric Item Characteristics Curve (ICC) for Suppression Items Using TestGraf98:**

Interpretation: All the five items of the variable suppression have item characteristic curves which are quite monotonous and desirably display high discrimination capability of the respondants with rise in ability.

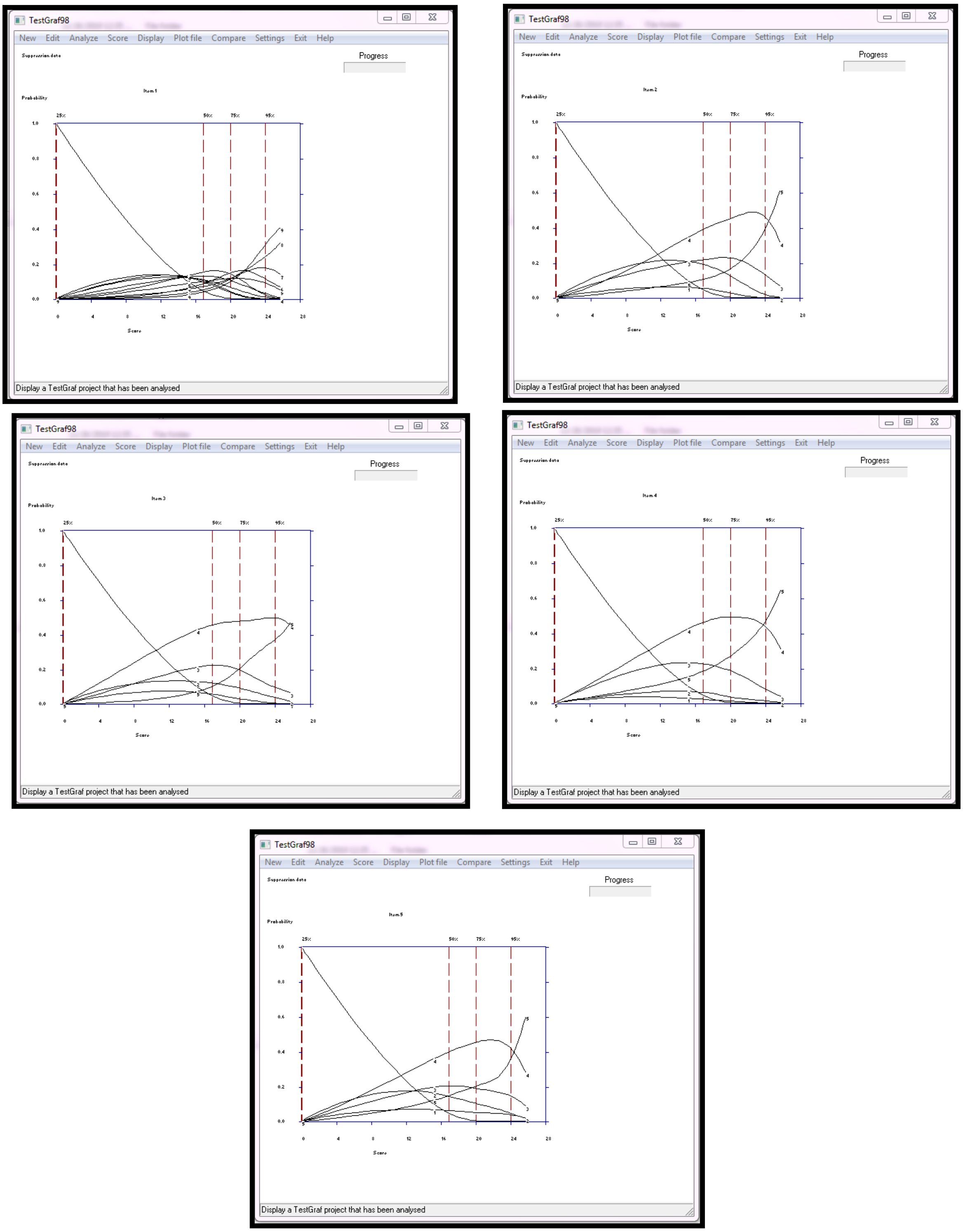


Figure 4.220 **Non Parametric Option Characteristic Curves (OCC) Suppression Items using TestGraf98:**

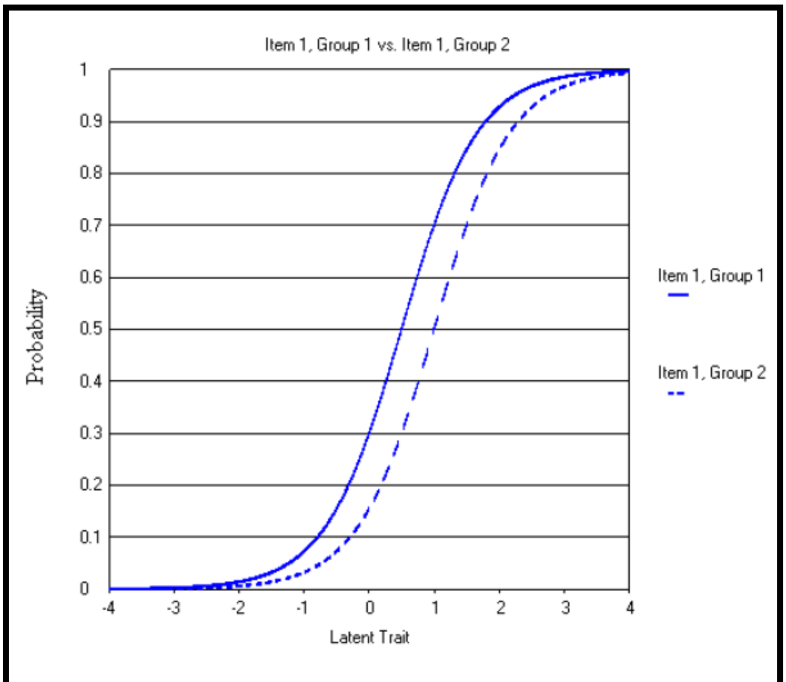
Conclusion: The smoothing parameter "h" is the pivotal estimate which determines how the curves would emerge through kernel smoothing technique, followed by the extent of their smoothness. The default value of 0.24 of the software is often a conservative one through which curves generally do not get generated. This calls for a rise in the value of this parameter (Ramsay, 2000). However, it is to be noted that higher the h value, more the information is lost regarding the curve. All the above displayed NIRT based ICC and OCC curves of the 14 variables were generated when the h value was raised to 0.6. There is a sparcity of statistics in the NIRT carried out by TestGraf98 as the software generates visual outputs only (Marcoulides and Moustaki, 2012).

4.4.1 Differential Item Functioning (DIF) of the Items Using EasyDIF Software – Item Response Theory (IRT) Framework based Measurement Invariance of the Items with respect to Gender:

According to Putnick andBornstein (2016), measurement invariance testing can either be based on Item Response Theory (IRT) framework or based on Structural Equation Modeling (SEM) framework using Confirmatory Factor Analysis (CFA). In the present study, the items selected for the final instrument to measure self regulated learning are made to undergo IRT based framework of measurement invariance with respect to gender. Then, the SEM based framework has been used to test the measurement invariance of the revised integrative trait model of self regulated learning among engineering undergraduates, with respect to gender, stream and batch. In this way, both the known approaches of measurement invariance testing are brought to use in this study.

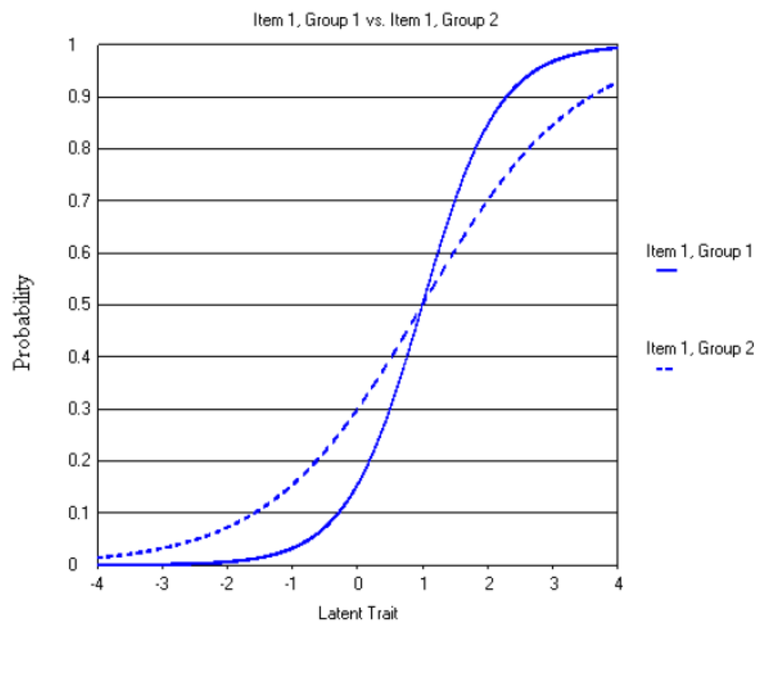
Ensuring the measurement invariance of an item across different groups based on gender, culture or ethnicity is done through the statistical technique of Differential Item Functioning Analysis (DIF) (Tay, Meade and Cao, 2015). It is one of the means of validation of psychological instruments. According to Guilera, Gomez-Benito and Hidalgo (2009), "an item is considered to display DIF when subjects from different groups (e.g., ethnicity, culture or gender) have a different probability of endorsing an item, when these are matched on the attribute measured by the item." When participants from two separate groups possess same level of a latent trait in them, but the probability of chosing responses of an item measuring the latent trait by these participants differ, then the item is said to be showing differential item functioning (Kahraman, DeBoeck and Janssen, 2009; Holland and Thayer, 1988; Roussos and Stout, 2004; Penfield and Camilli, 2007) posing threat to comparability of scores of the measured trait across groups. The definition of DIF in ability measurement is different from the DIF definition in attitude measurement (Dodeen, 2004). In attitude DIF measurement, a significance test is conducted to infer whether an item possesses DIF.

According to Shealy and Stout (1993) DIF happens because an item not only measures the factor of interest, but also has the capability of measuring another closely related factor. As a result, while the subjects from two different groups may be same as per the primary factor of interest, but differ in the closely related factor and this difference is manifested in the display of differential item functioning of the item (Gierl,2005).



Source: Zwick, Donoghue and Grima (1993)

Figure 4.221 **An item with uniform DIF**



Source: Zwick, Donoghue and Grima (1993)

***Figure 4.222*An item with non-uniform DIF**

There are two types of DIF, namely uniform and non-uniform. In uniform DIF, the probability of item endorsement by subjects of a group is higher than the subjects of another group all along the levels of the scale. In non-uniform DIF, the probability of item endorsement by subjects of a group exists up to a certain level of measurement, there after taken over by the subjects from another group for the remaining higher levels (Ibrahim, 2017; Salkind, 2007).

DIF for polytomous items is performed using the Mantel-Haenszel chi-square (1959) procedure by a freely available software known as EASYDIF (Kumagai, 2012). The software estimates the Mantel statistics for ordinal data (Mentel, 1963), the probability value and its standardized difference, apart from generating the graphical representation of DIF of an item across both the groups (Gonzalez et al., 2010). The presence of DIF using EASYDIF is found with the help of K-index developed by Kumagai (2012). When the K-index generated by the software (using Thissen’s method (Thissen, Steinberg and Wainer, 1993) and SIBTEST (Shealy and Stout,1993)) is shown in red, it implies that the item possesses differential item functioning. The interpretation of K index is done using the formula "(Number of categories - 1)*0.1". If index K is greater than this value, then it is assumed that DIF is large. For example, K-index will be large, when for a seven point Likert scale, its value if greater tha (7-1)*0.1=0.6.

The differential item functioning curves and the K-index for the items of certain the self regulated learning variables are as follows:

i. Crtical Thinking

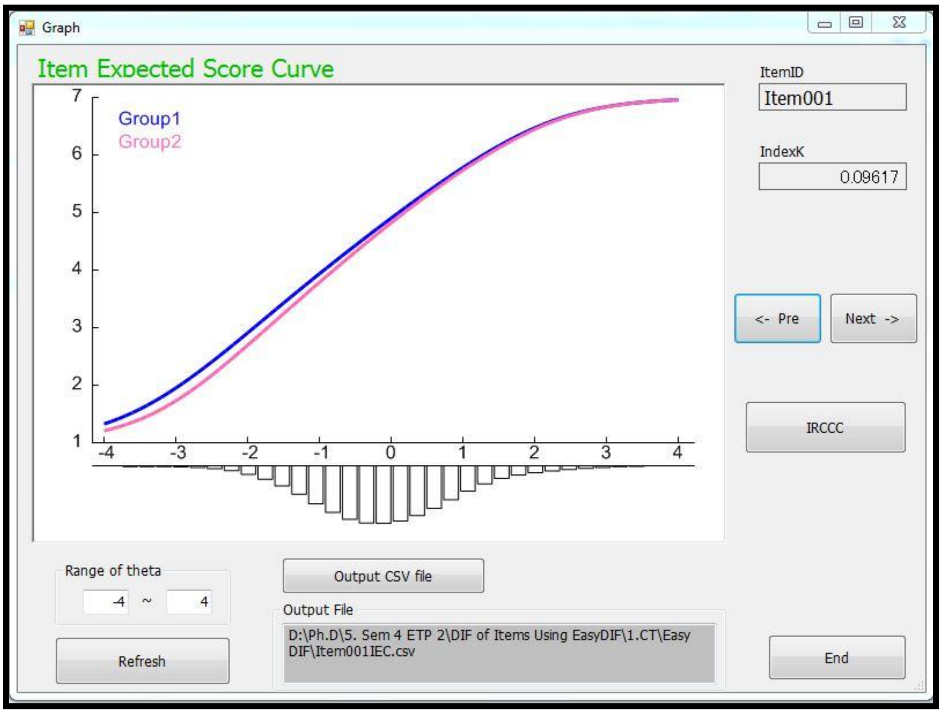


Figure 4.223 **DIF of Critical Thinking – Item 1**

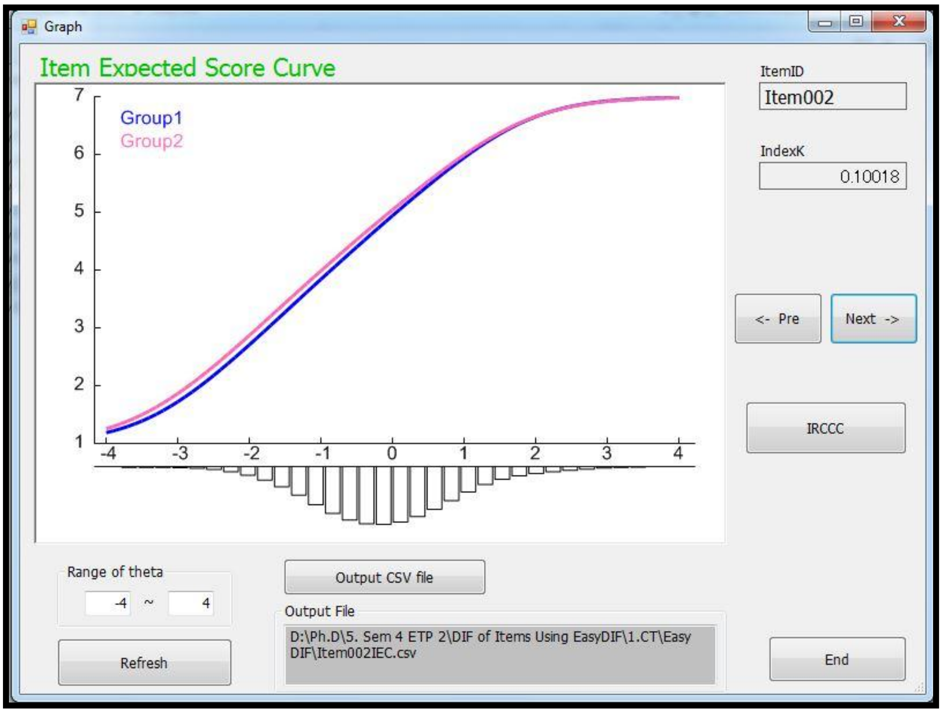


Figure 4.224 **DIF of Critical Thinking – Item 2**

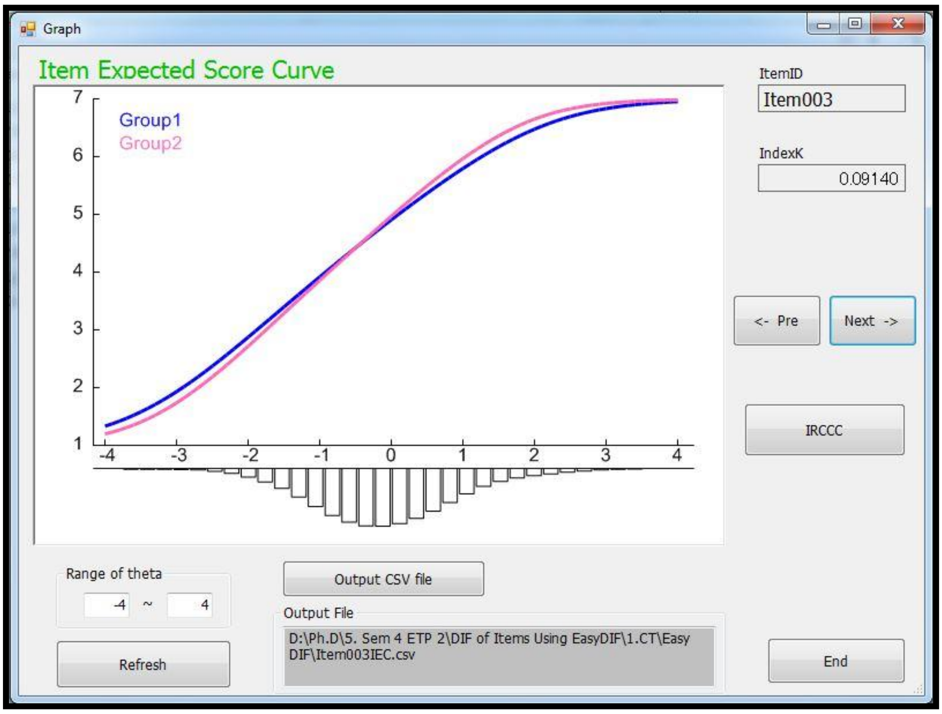


Figure 4.225 **DIF of Critical Thinking – Item 3**

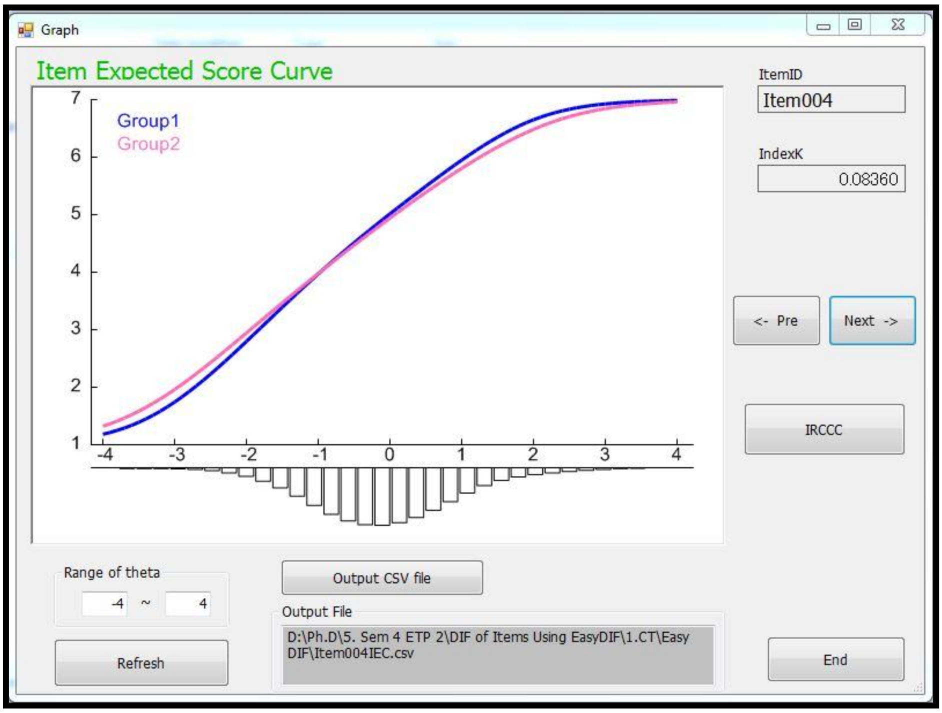


Figure 4.226 DIF of Critical Thinking – Item 4

Interpretation: The above items of critical thinking variable are part of the MSLQ (1991) scale with seven point likert scale responses. Here, the critical K-index is (7-1)*0.1=0.6. Since the generated K-values of all the four items is less than 0.6, desirably none of these items show differential item functioning with respect to gender.

ii. Organization

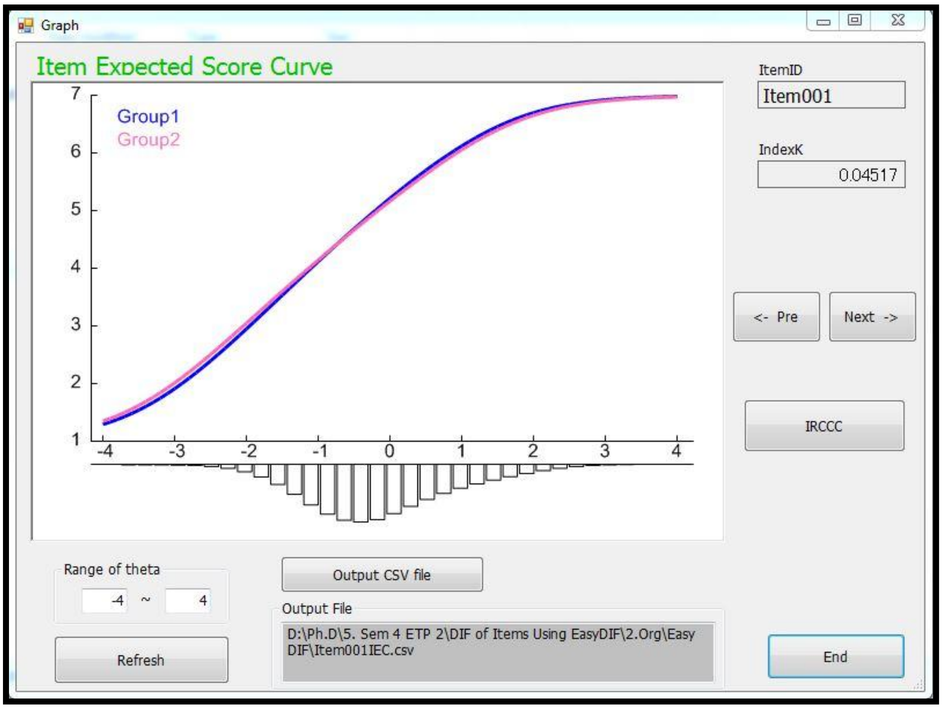


Figure 4.227 DIF of Organization – Item 1

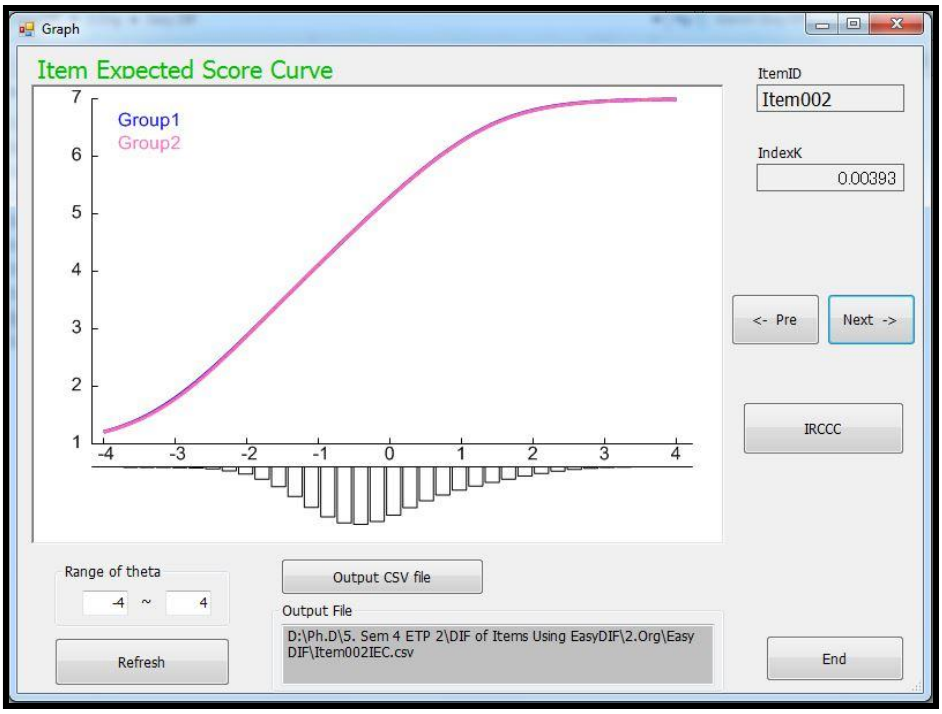


Figure 4.228 DIF of Organization – Item 2

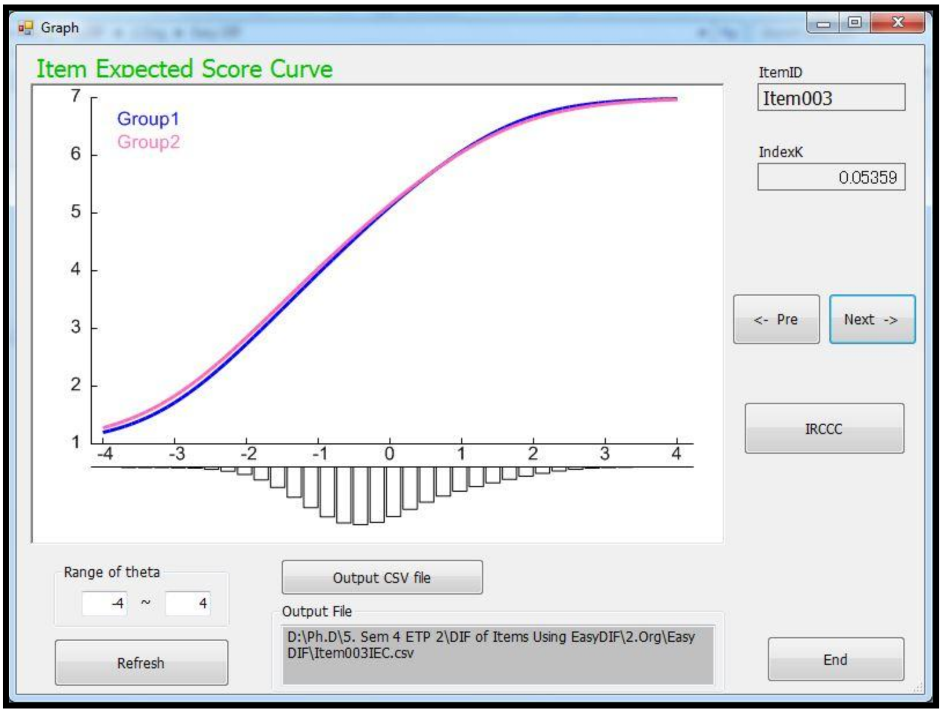


Figure 4.229 **DIF of Organization – Item 3**

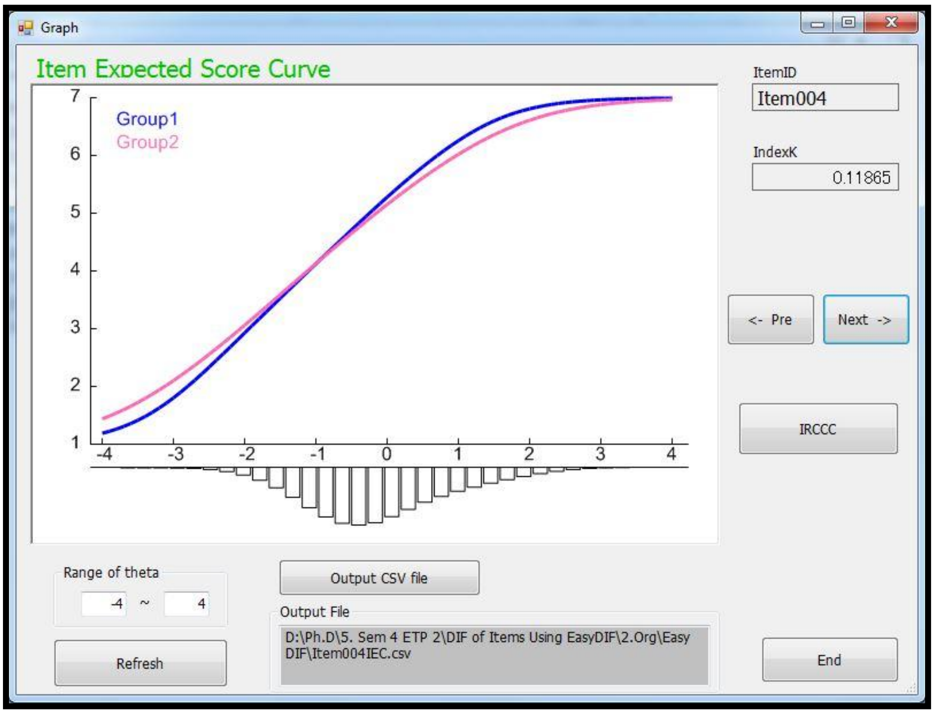


Figure 4.230 **DIF of Organization – Item 4**

Interpretation: The above items of organization variable are part of the MSLQ (1991) scale with seven point likert scale responses. Here, the critical K-index is (7-1)*0.1=0.6. Since the generated K-values of all the four items is less than 0.6, desirably none of these items show differential item functioning with respect to gender.

DIF of Items of Scale 3, 4 and 5 – Planning, Self recording and Self Evaluation could not be generated since the sample subjects of the pilot study were all males subjects pursing Mechanical engineering.

vi. Academic Intrinsic Motivation:

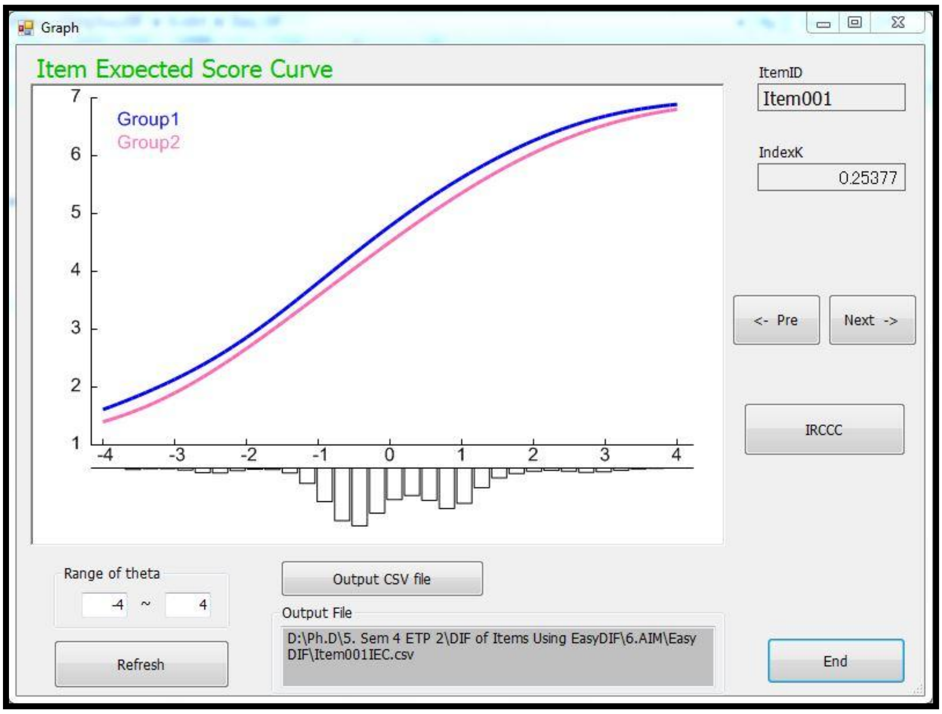


Figure 4.231 **DIF of Academic Intrinsic Motivation – Item 1**

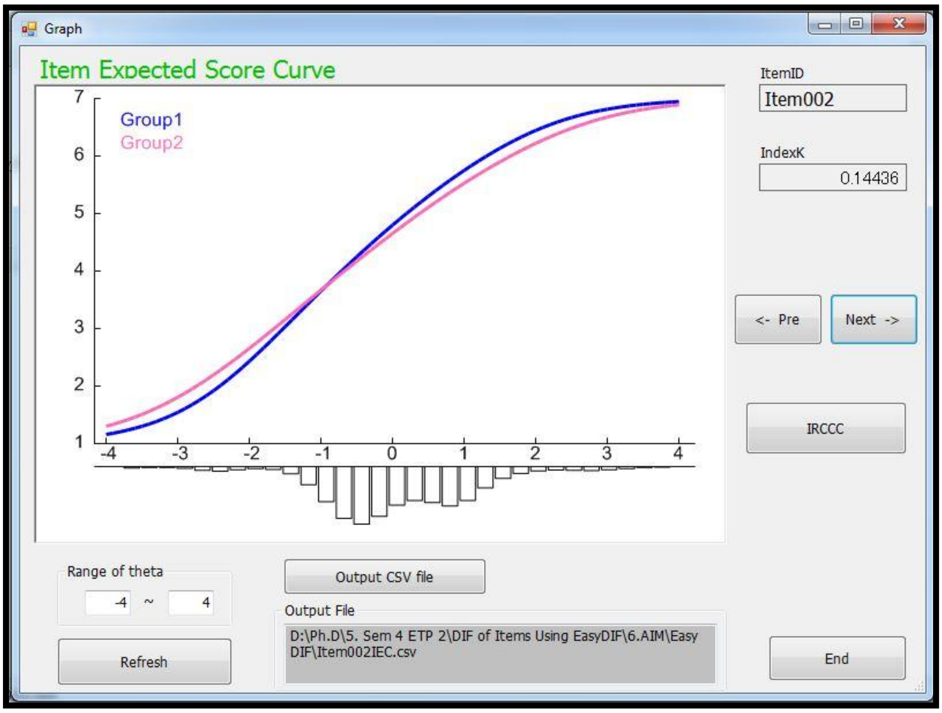


Figure 4.232 **DIF of Academic Intrinsic Motivation – Item 2**

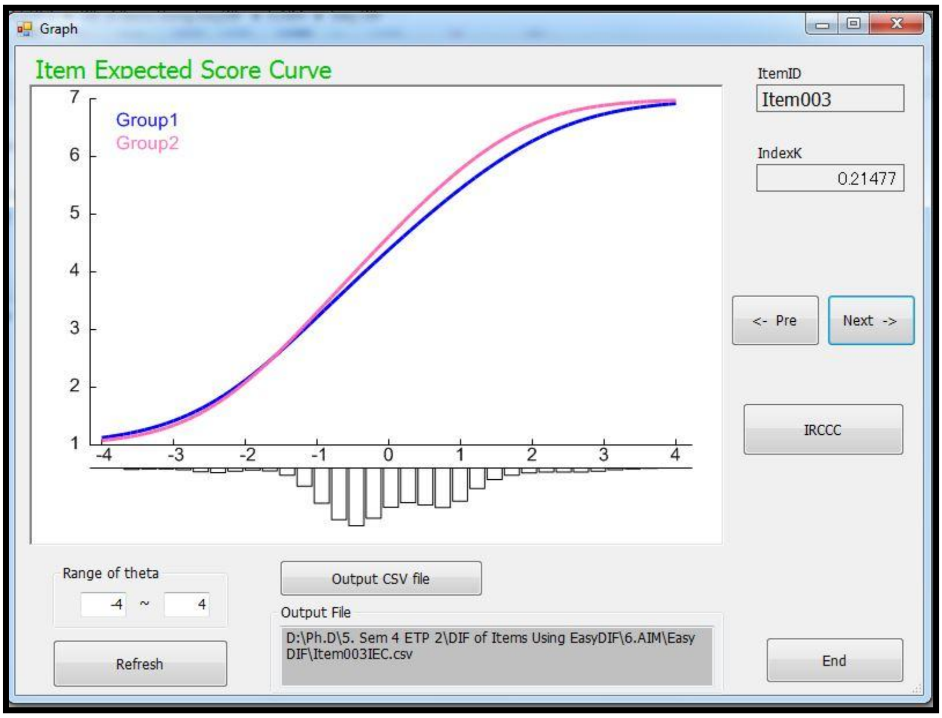


Figure 4.233 **DIF of Academic Intrinsic Motivation – Item 3**

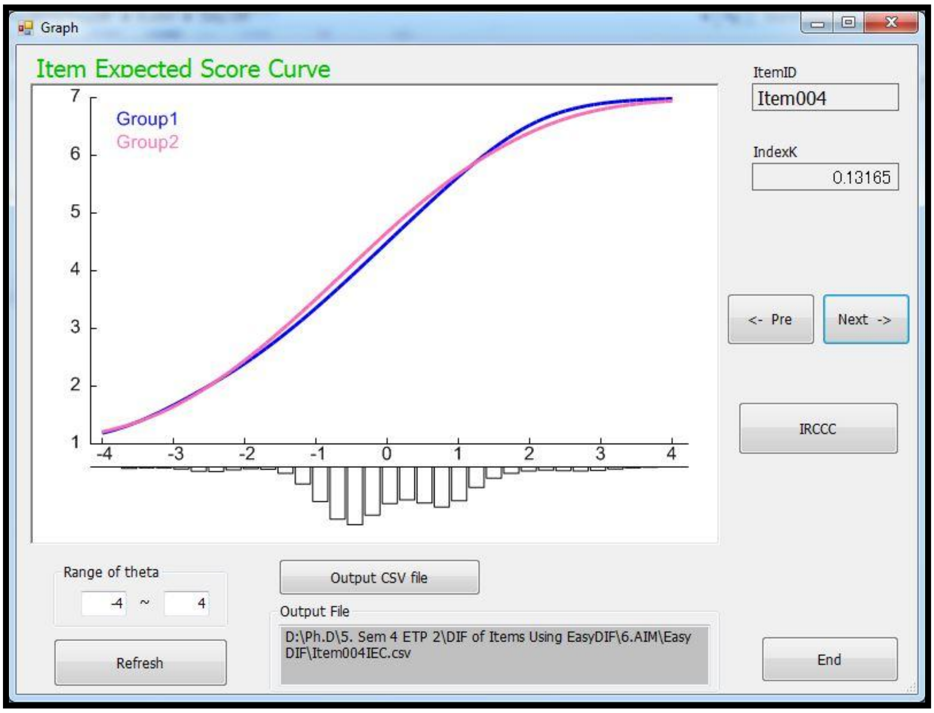


Figure 4.234 **DIF of Academic Intrinsic Motivation – Item 4**

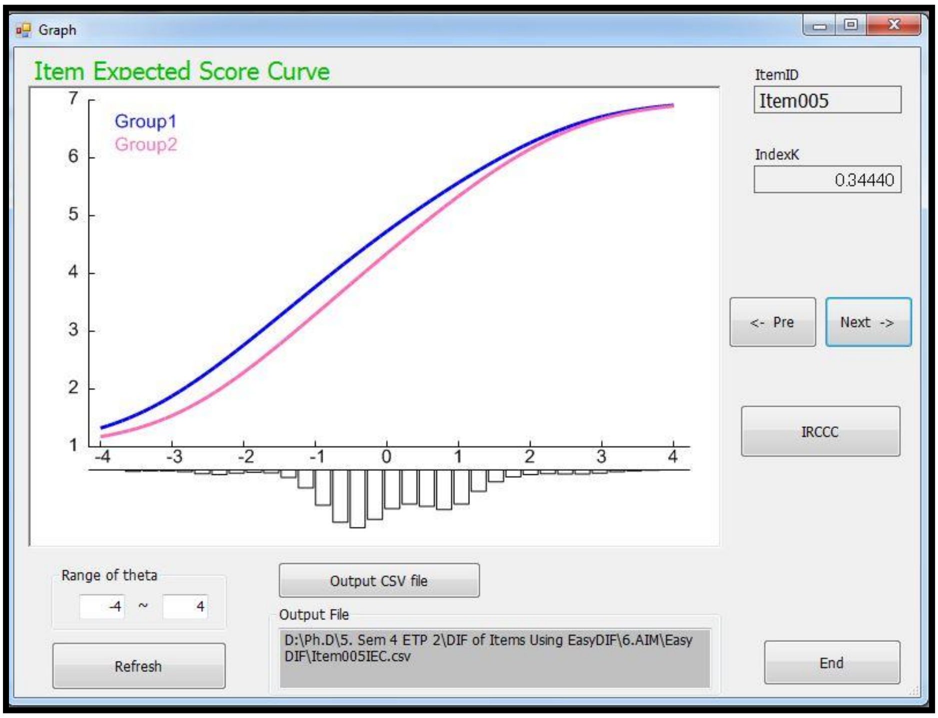


Figure 4.235 **DIF of Academic Intrinsic Motivation – Item 5**

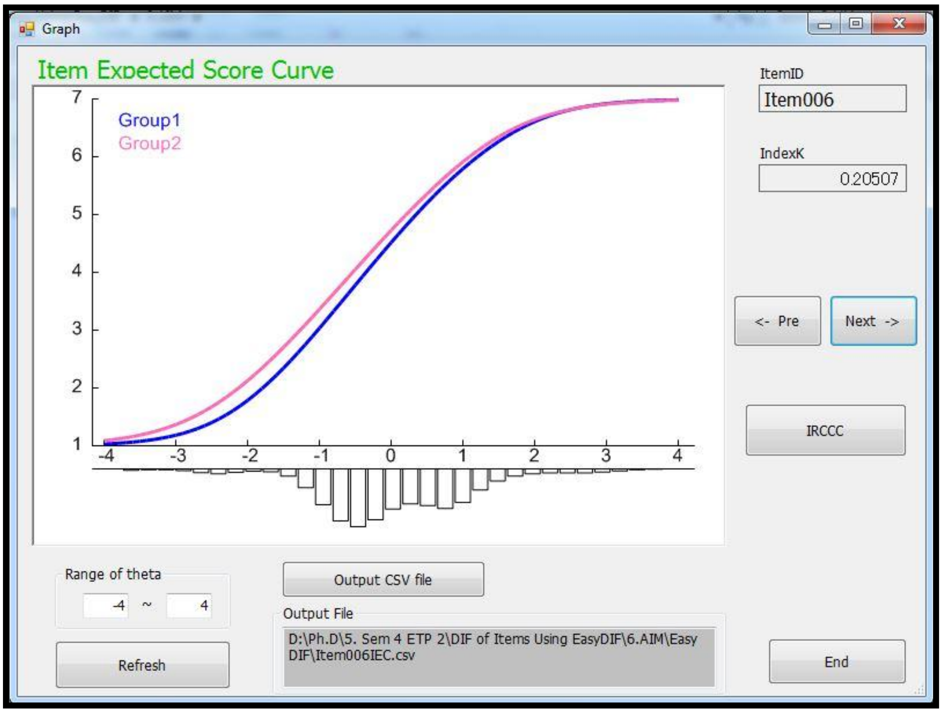


Figure 4.236 **DIF of Academic Intrinsic Motivation – Item 6**

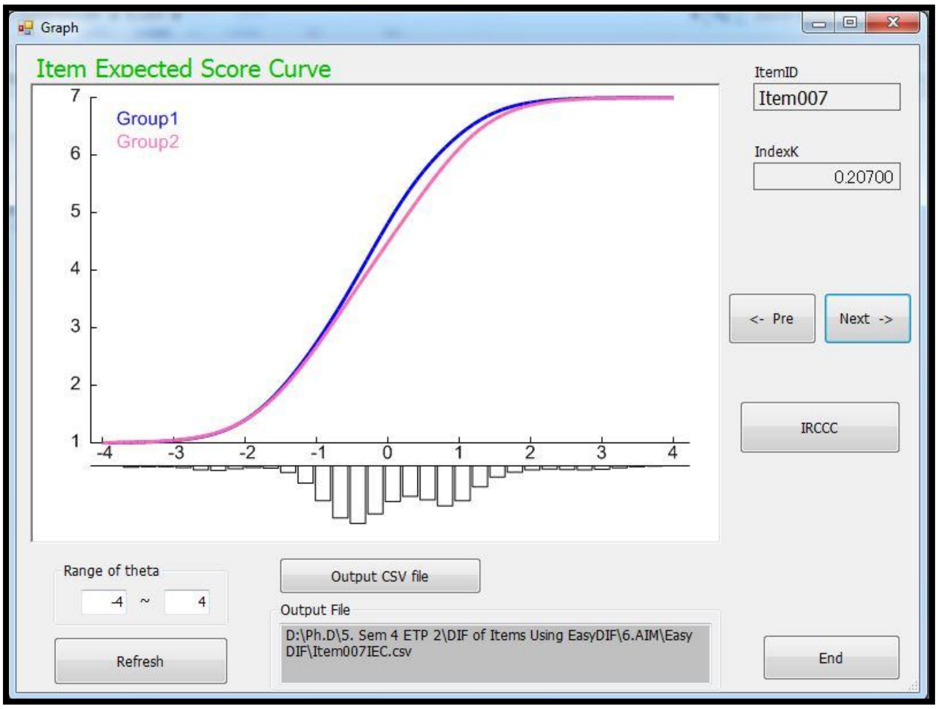


Figure 4.237 **DIF of Academic Intrinsic Motivation – Item 7**

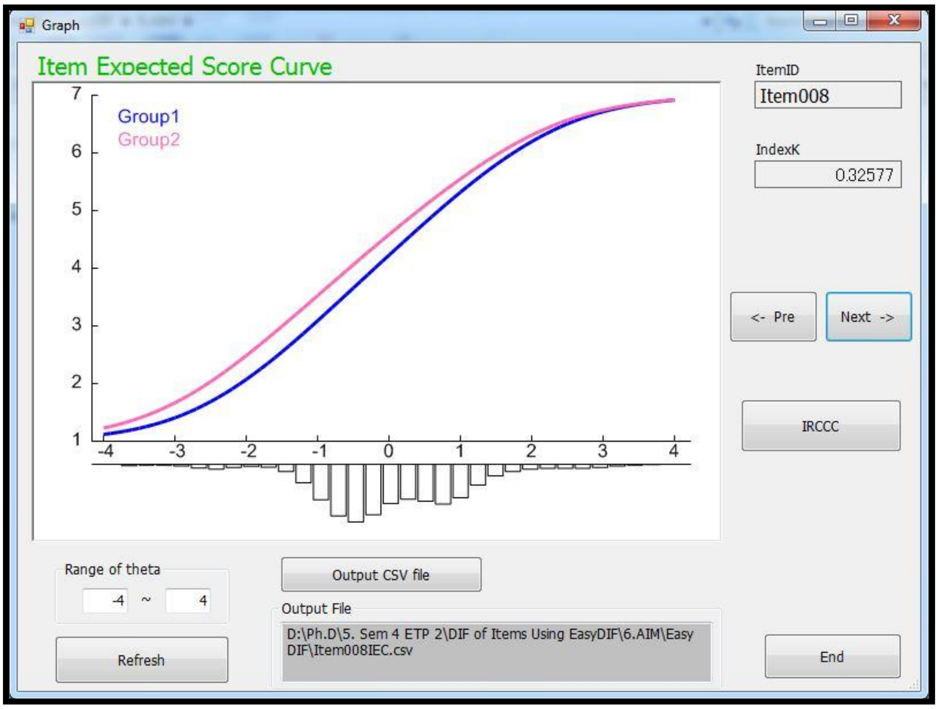


Figure 4.238 **DIF of Academic Intrinsic Motivation – Item 8**

Interpretation: The above items of academic intrinsic motivation variable are part of the AMS-28 (1992) scale with seven point likert scale responses. Here, the critical K-index is (7-1)*0.1=0.6. Since the generated K-values of all the eight items is less than 0.6, desirably none of these items show differential item functioning with respect to gender.

vii. Self Efficacy

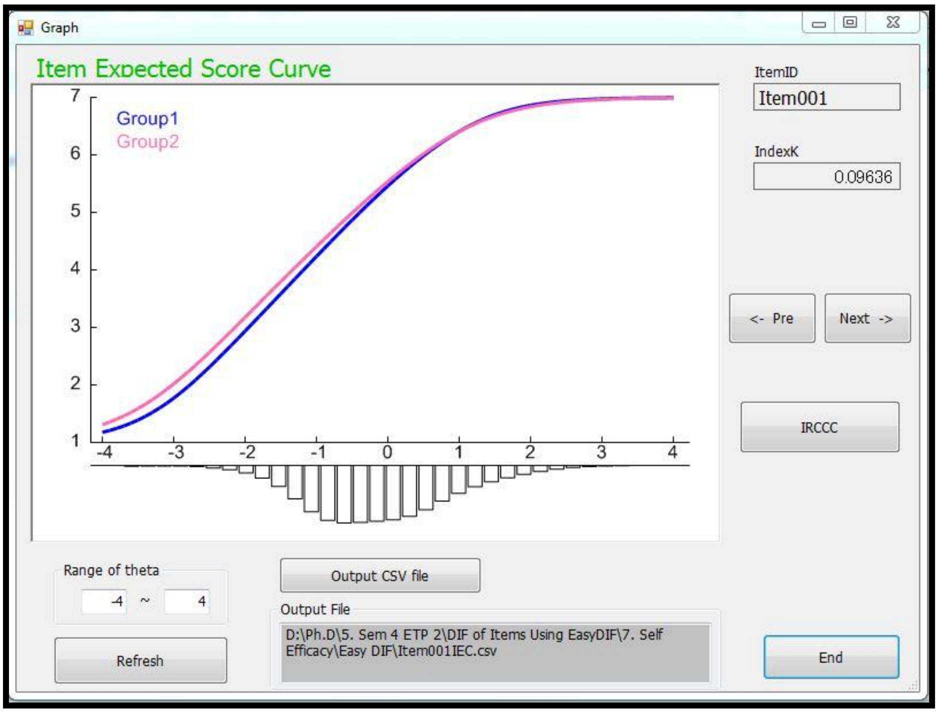


Figure 4.239 **DIF of Self Efficacy – Item 1**

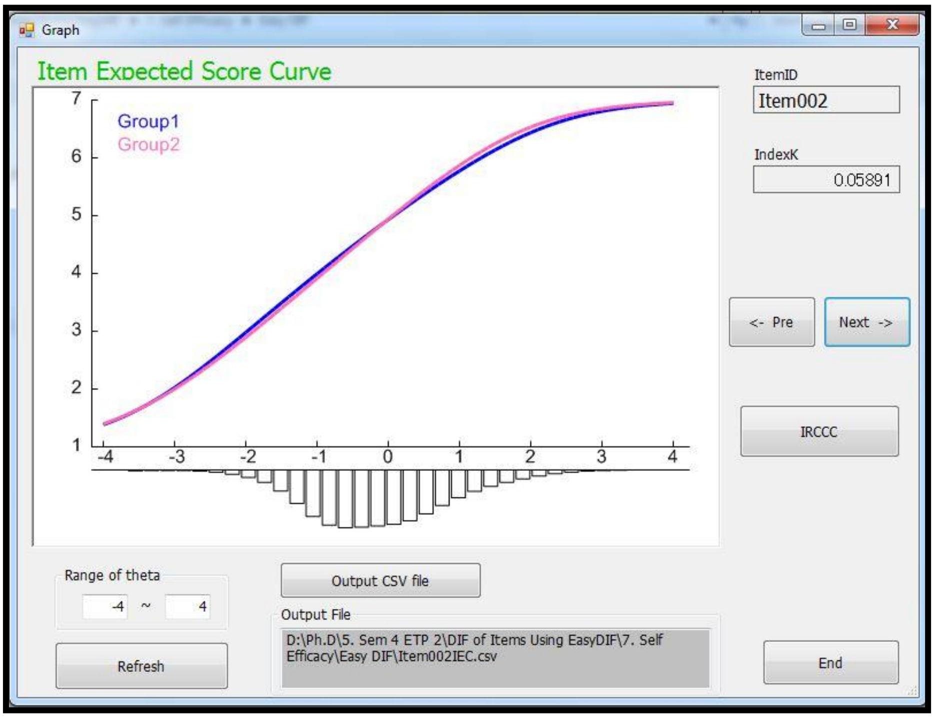


Figure 4.240 **DIF of Self Efficacy – Item 2**

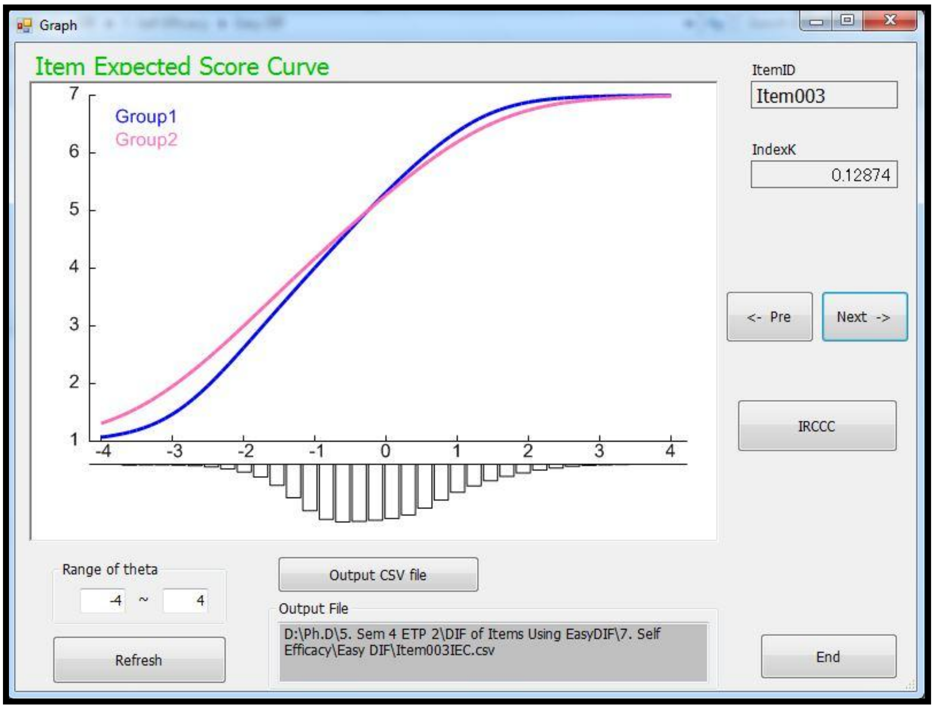


Figure 4.241 **DIF of Self Efficacy – Item 3**

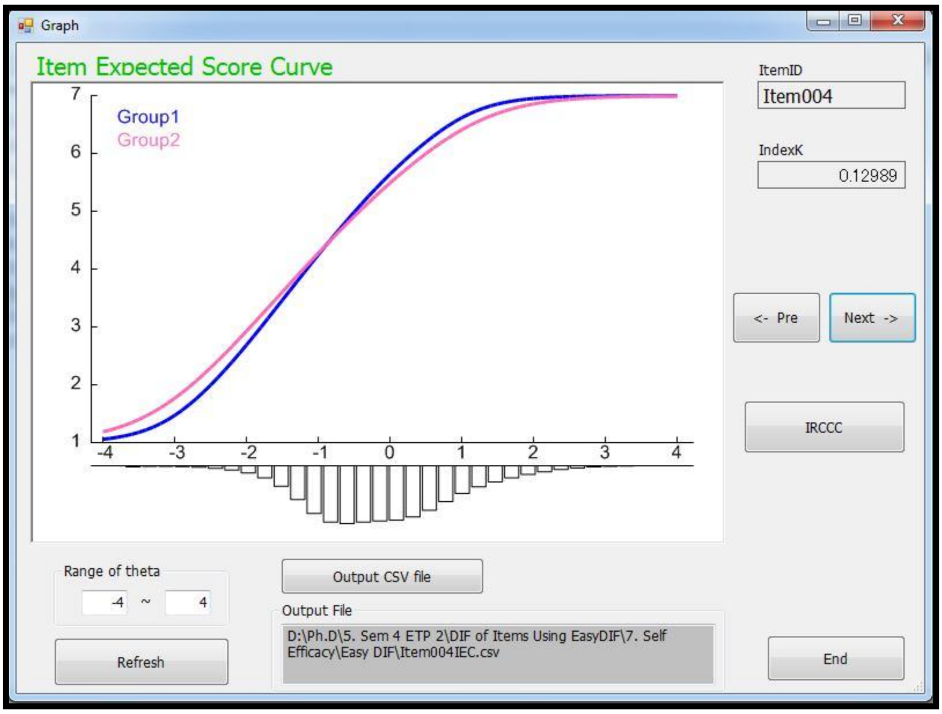


Figure 4.242 **DIF of Self Efficacy – Item 4**

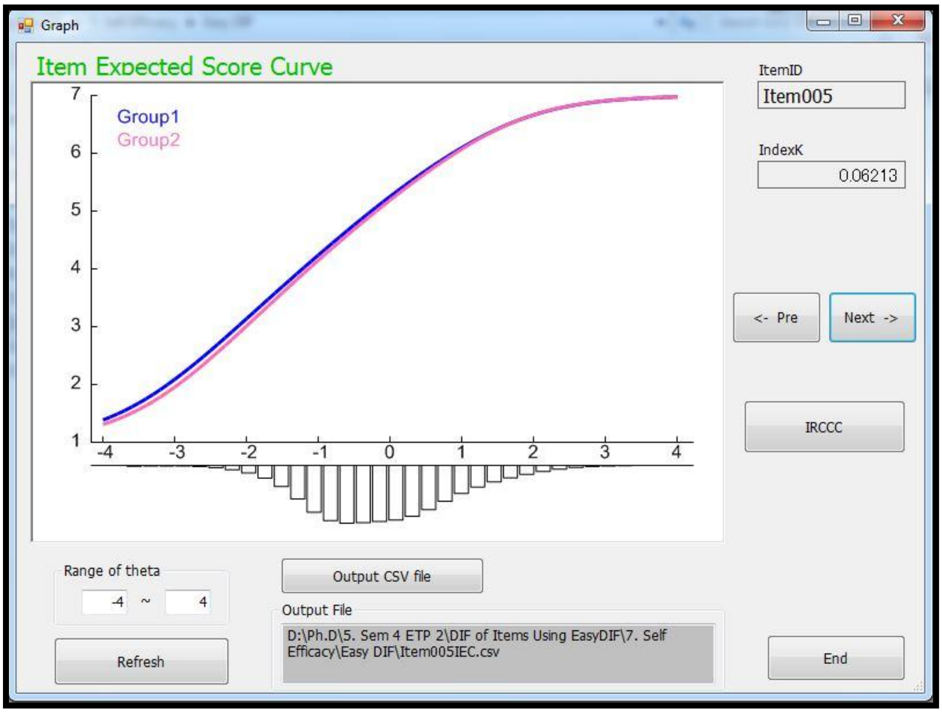


Figure 4.243 DIF of Self Efficacy – Item 5

Interpretation: The above items of self efficacy variable are part of the MSLQ (1991) scale with seven point likert scale responses. Here, the critical K-index is (7-1)*0.1=0.6. Since the generated K-values of all the five items is less than 0.6, desirably none of these items show differential item functioning with respect to gender.

viii. Goal Orientation

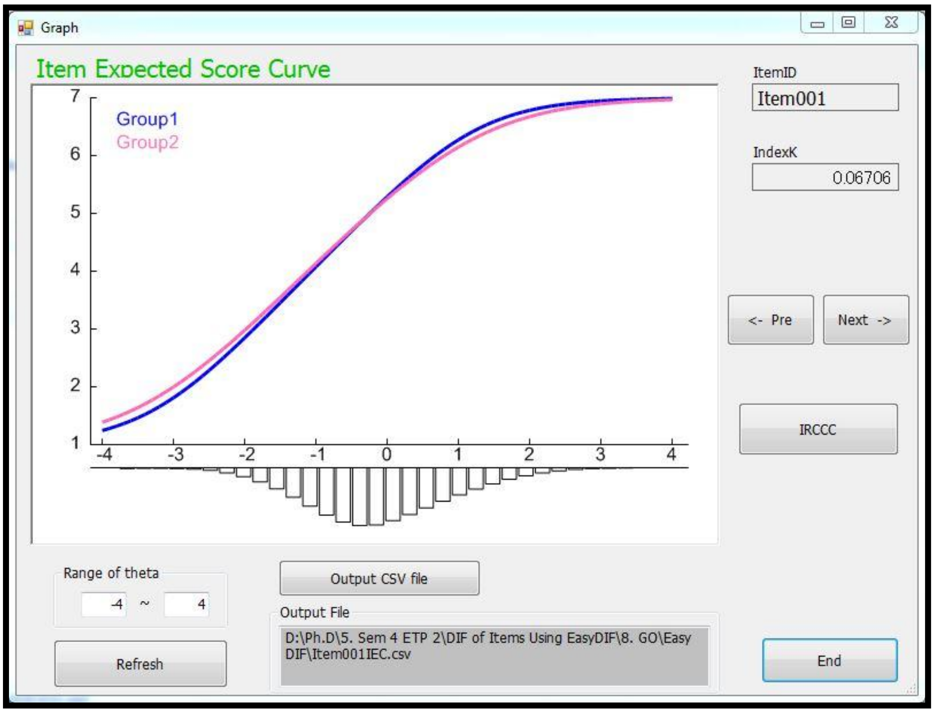


Figure 4.244 **DIF of Goal Orientation – Item 1**

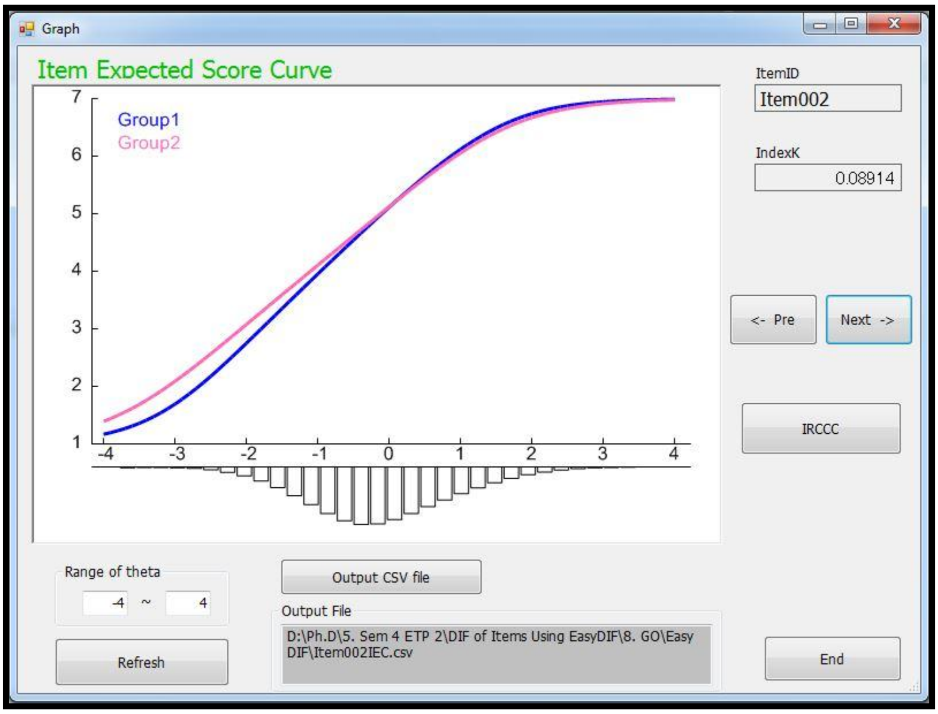


Figure 4.245 **DIF of Goal Orientation – Item 2**

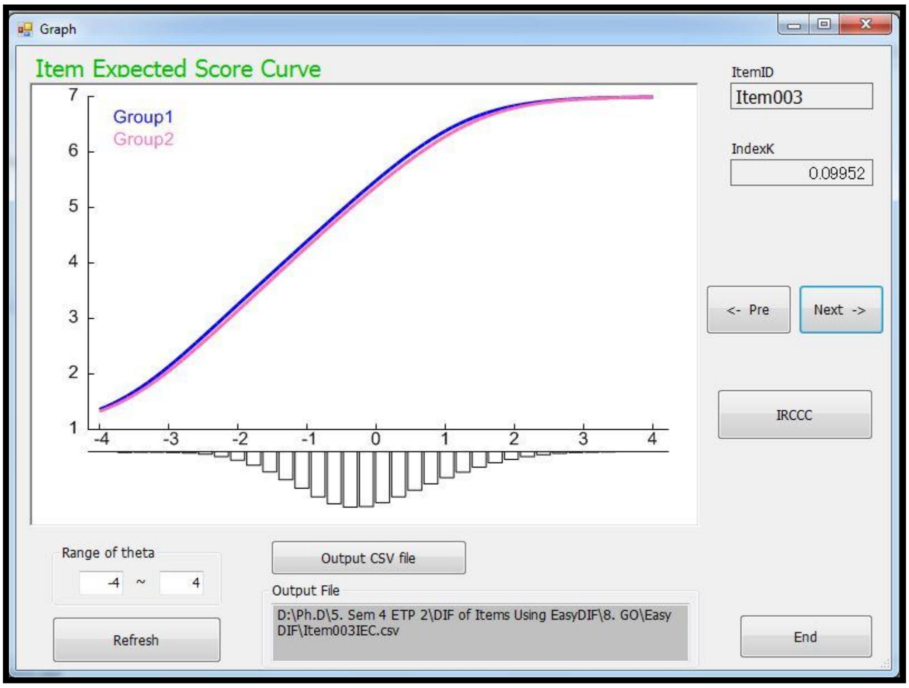


Figure 4.246 **DIF of Goal Orientation – Item 3**

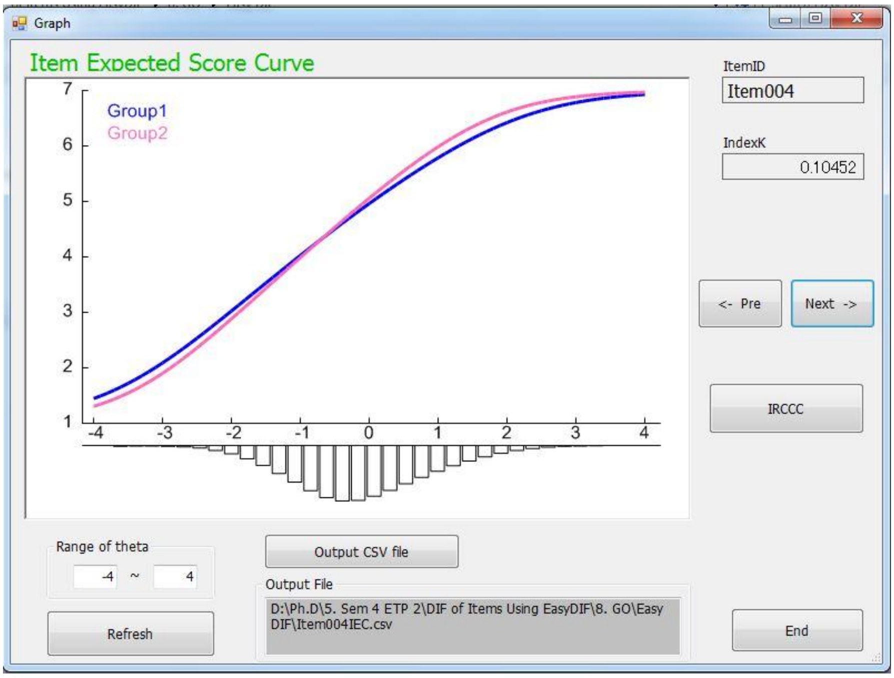


Figure 4.247 **DIF of Goal Orientation – Item 4**

Interpretation: The above items of goal orientation variable are part of the MSLQ (1991) scale with seven point likert scale responses. Here, the critical K-index is (7-1)*0.1=0.6. Since the generated K-values of all the four items is less than 0.6, desirably none of these items show differential item functioning with respect to gender.

ix. Academic Delay of Gratification

DIF of Items of Scale 9 – Academic Delay of Gratification:

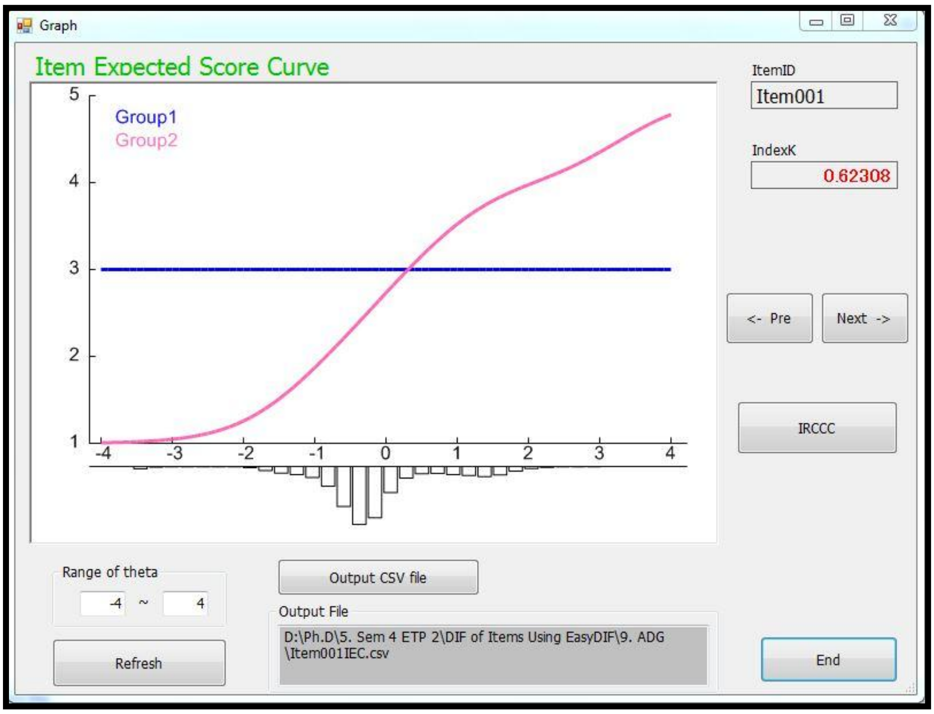


Figure 4.248 **DIF of Academic Delay of Gratification – Item 1**

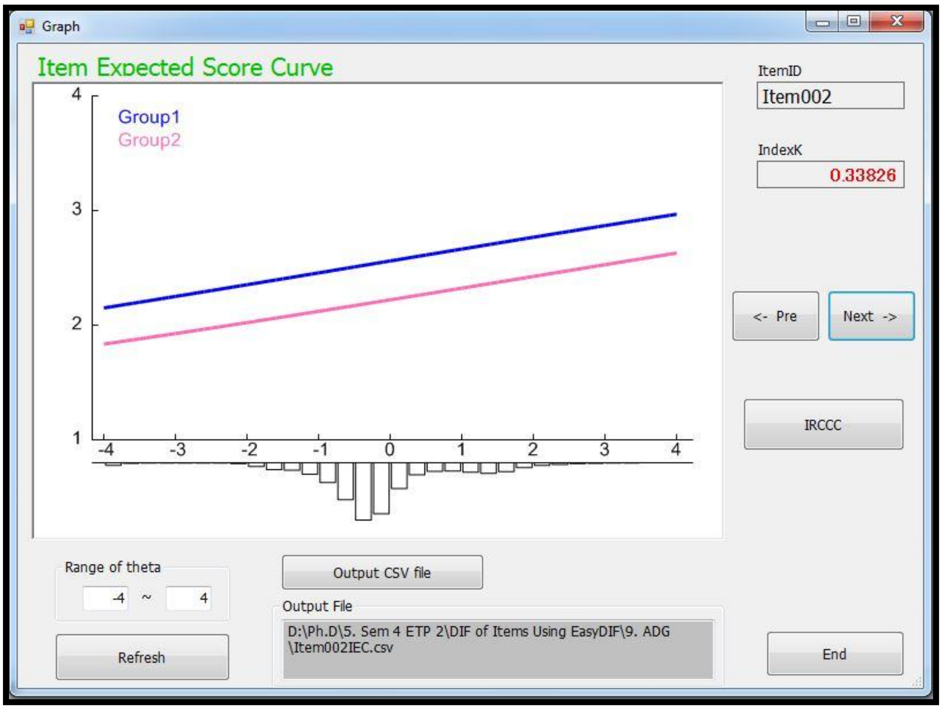


Figure 4.249 **DIF of Academic Delay of Gratification – Item 2**

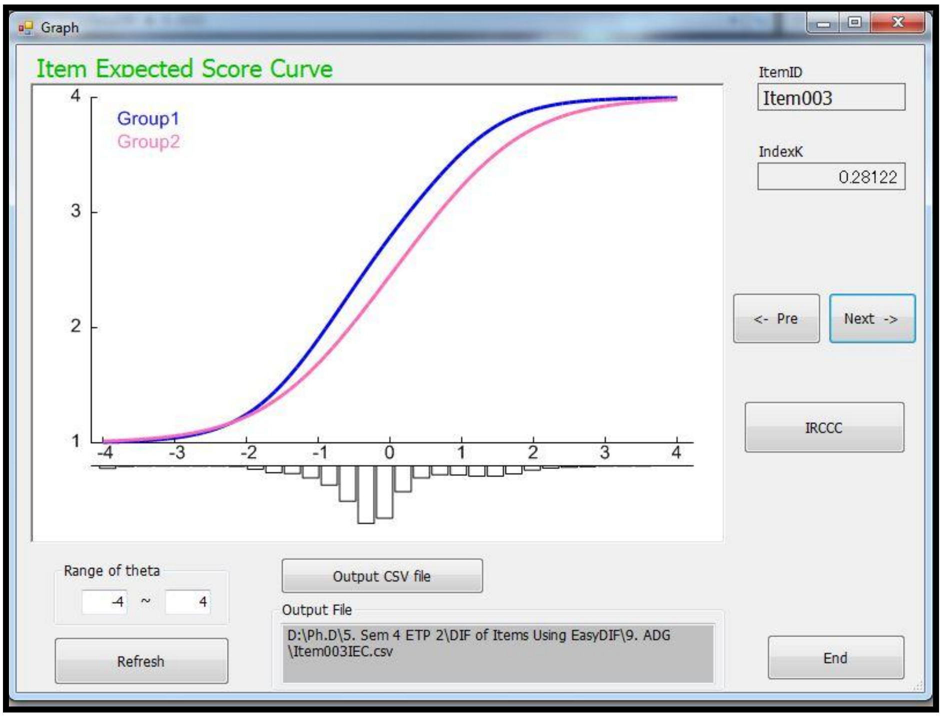


***Figure 4.250*DIF of Academic Delay of Gratification – Item 3**

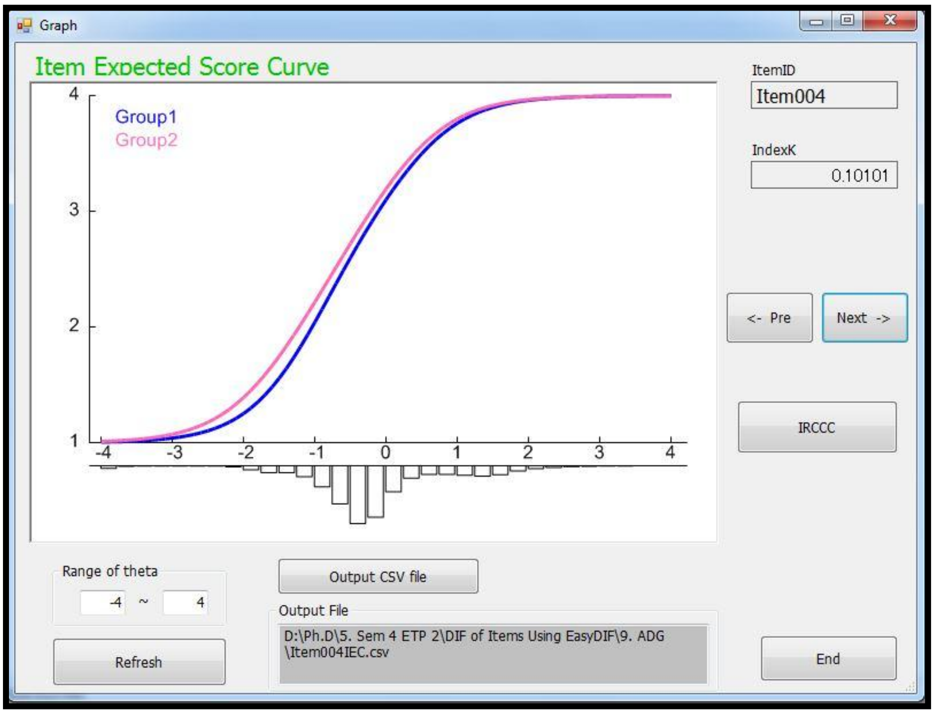


***Figure 4.251*DIF of Academic Delay of Gratification – Item 4**

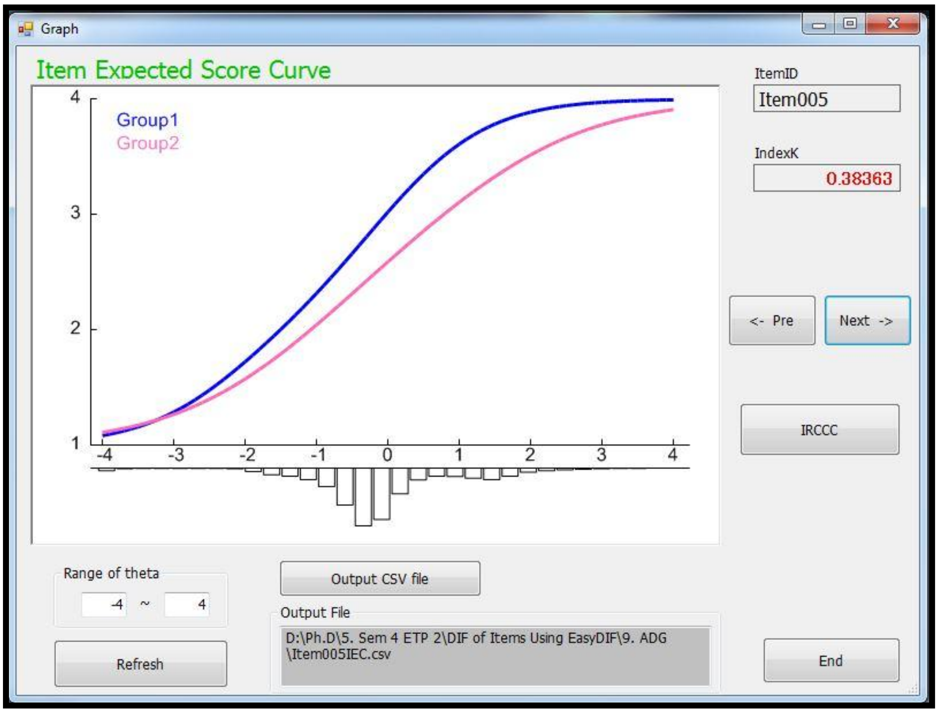


*Figure 4.252*DIF of Academic Delay of Gratification – Item 5

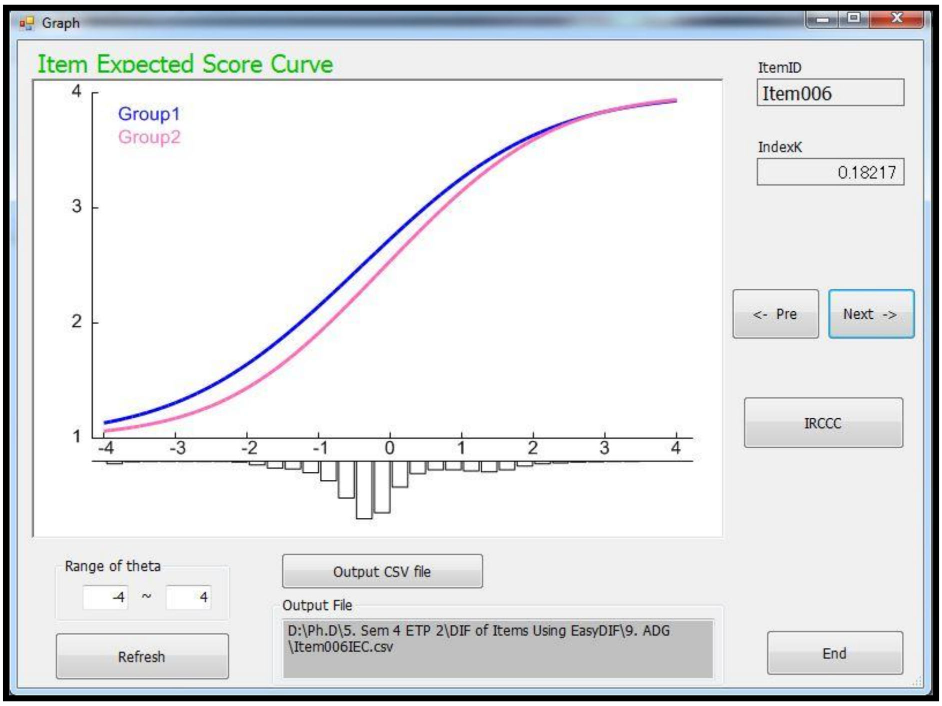


*Figure 4.253*DIF of Academic Delay of Gratification – Item 6

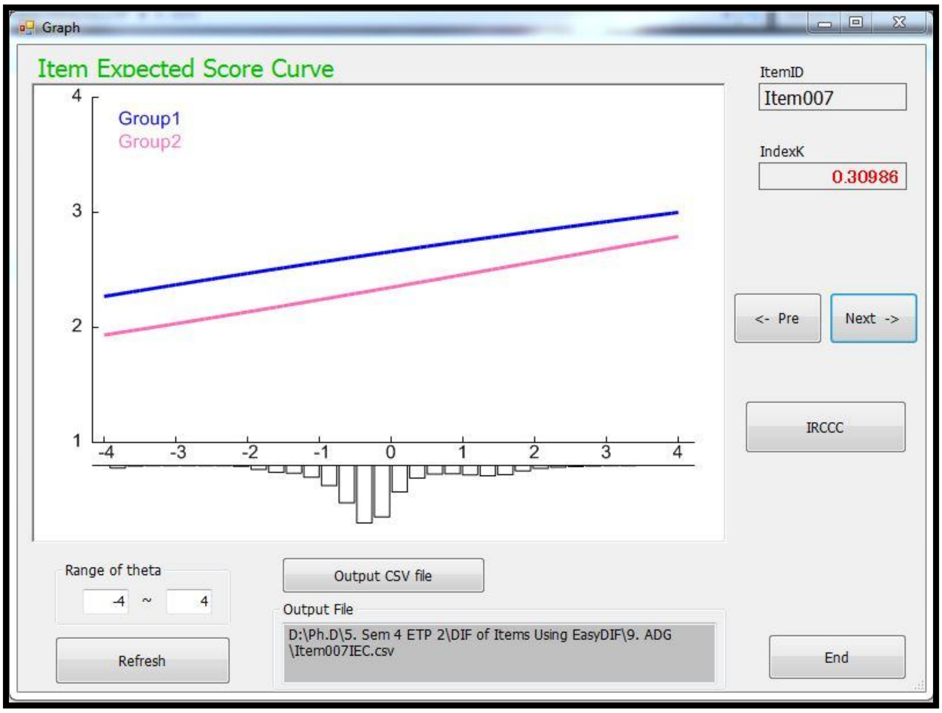


***Figure 4.254*DIF of Academic Delay of Gratification – Item 7**

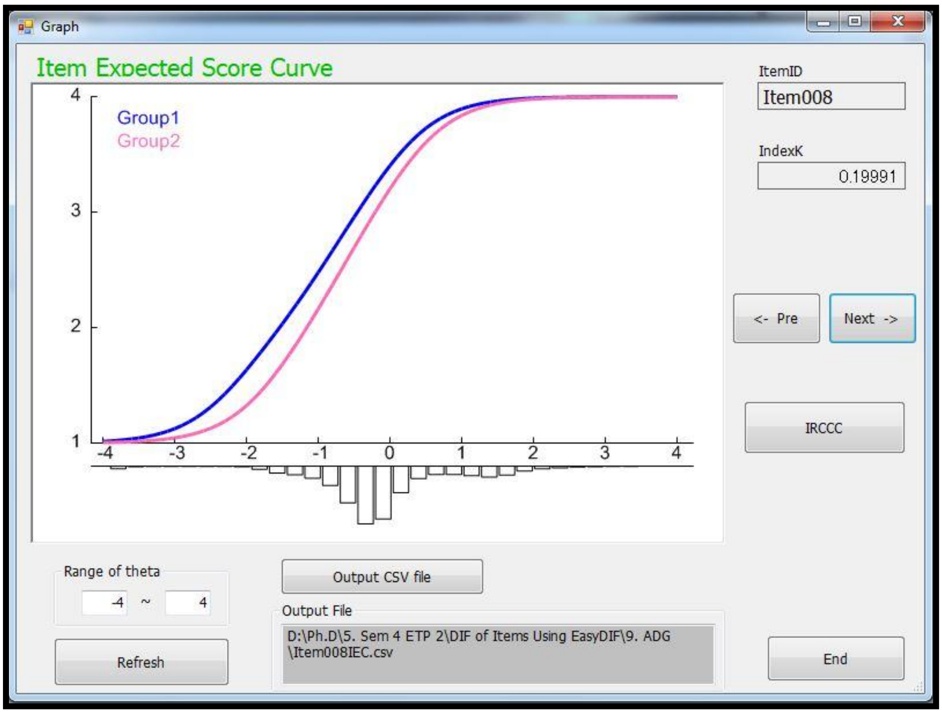


***Figure 4.255*DIF of Academic Delay of Gratification – Item 8**

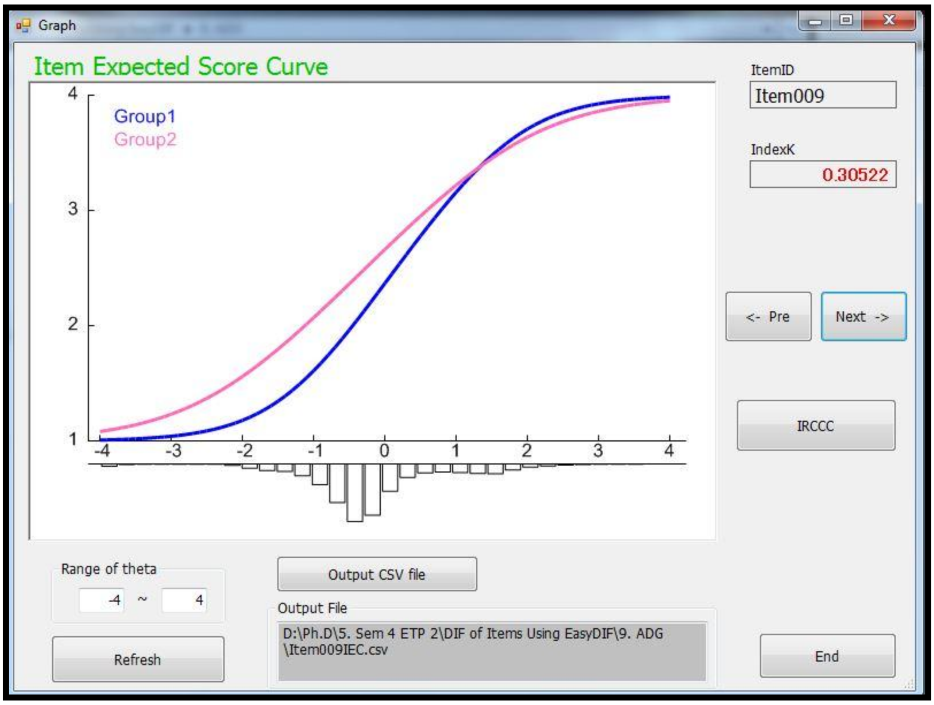


Figure 4.256**DIF of Academic Delay of Gratification – Item 9**

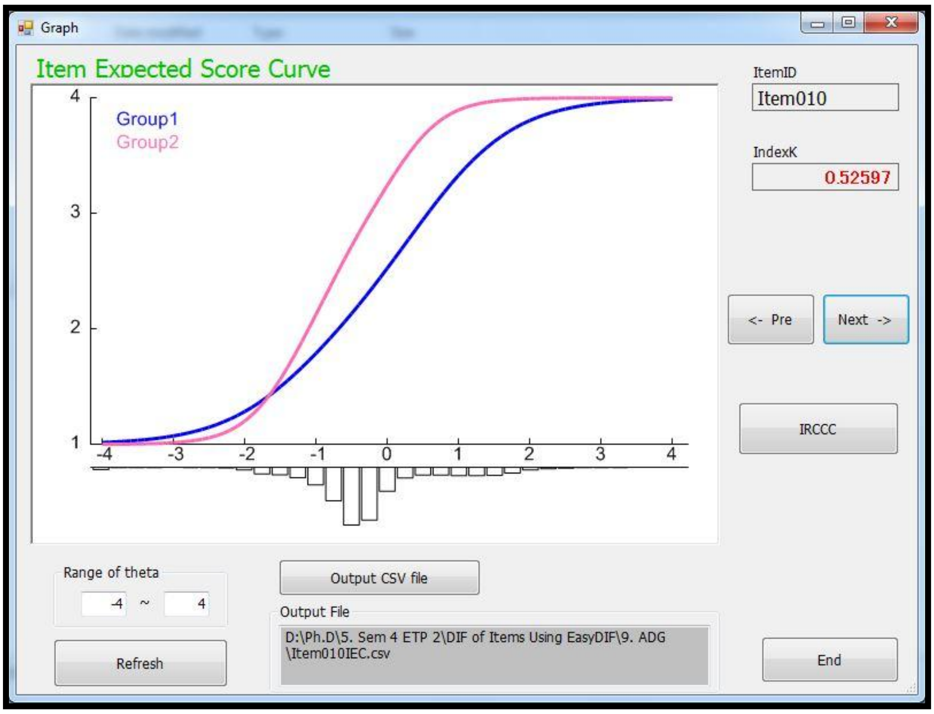


Figure 4.257**DIF of Academic Delay of Gratification – Item 10**

Interpretation: The above items of academic delay of gratification variable are part of the ADGS (1996) scale with four point likert scale responses. Here, the critical K-index is (4-1)*0.1=0.3. The K-index of items 1, 2, 5, 7, 9 and 10 are 0.62308, 0.33826, 0.38363, 0.30986, 0.30522, 0.5257 respectively, which are values greater than the critical value 0.3 for this scale. Hence, these items exhibit differential ite, functioning with respect to gender. The K-index of the items 3,4 6 and 8 are 0.28122, 0.10101, 0.19991, which are values less than 0.3 and hence these items desirably not know show DIF. Item 9 with K-index 0.30522 can be treated to be partially displaying DIF.Based on these results, only items 4, 8 and 9 of academic delay of gratification scale will be included in the final data analysis.

x. Academic Procrastination

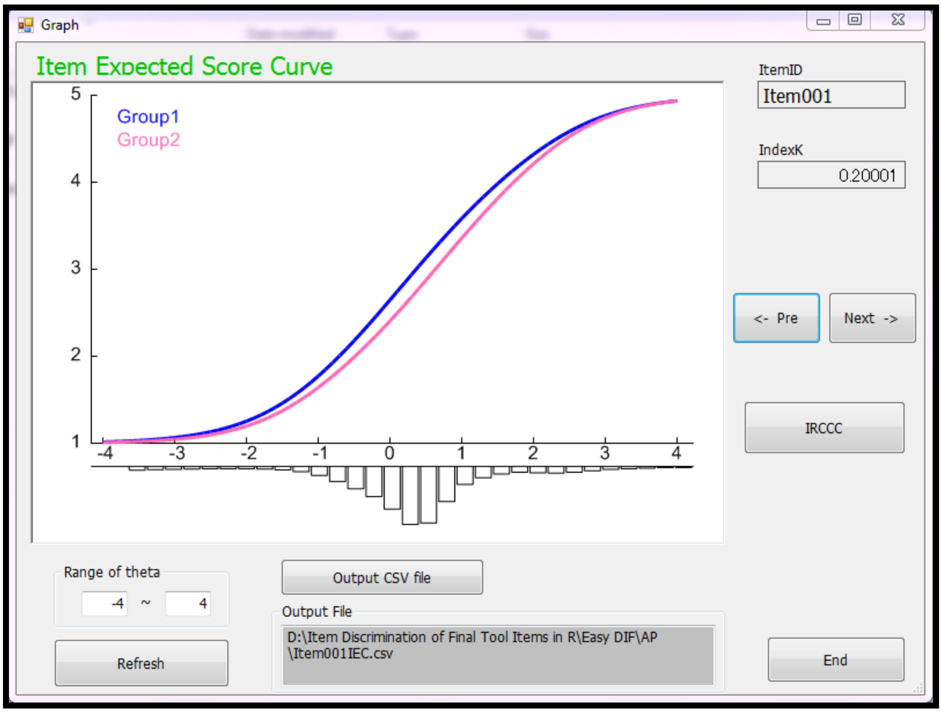


Figure 4.258**DIF of Academic Procrastination – Item 1**

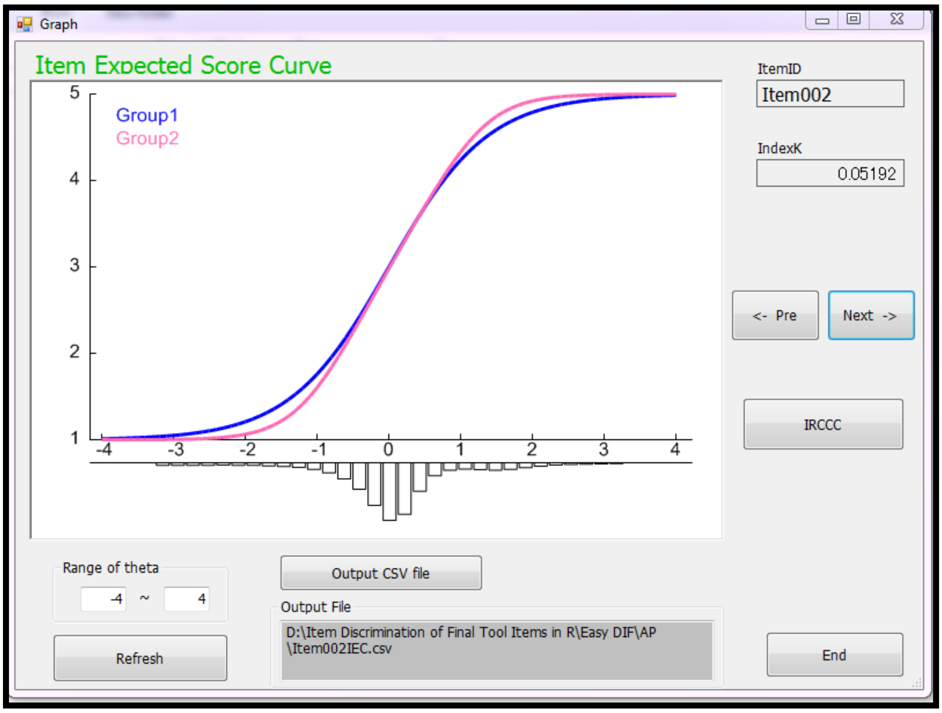


Figure 4.259**DIF of Academic Procrastination – Item 2**

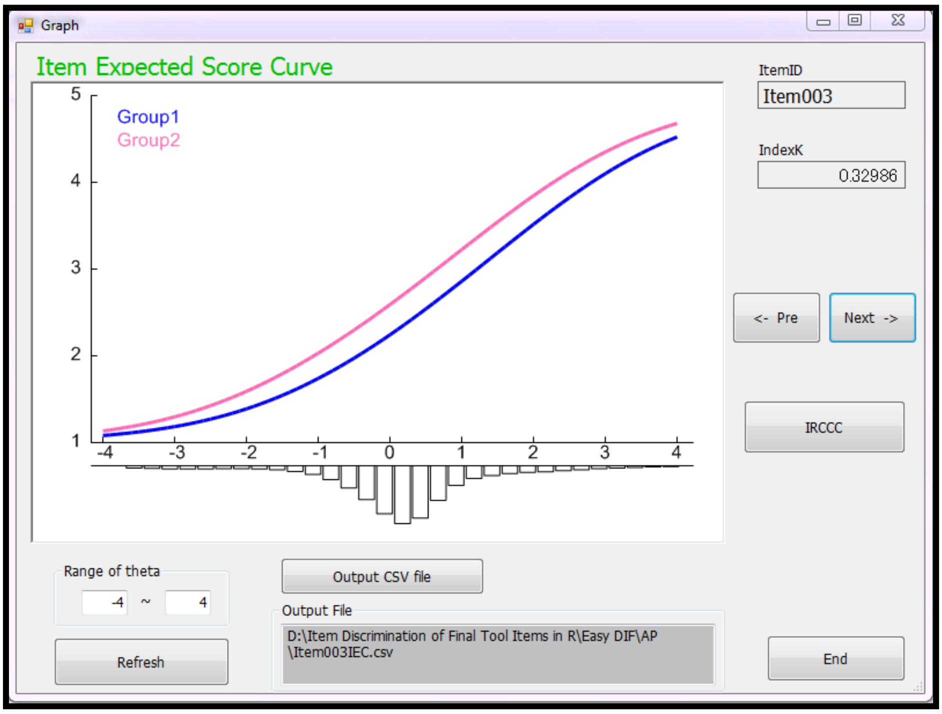


Figure 4.260**DIF of Academic Procrastination – Item 3**

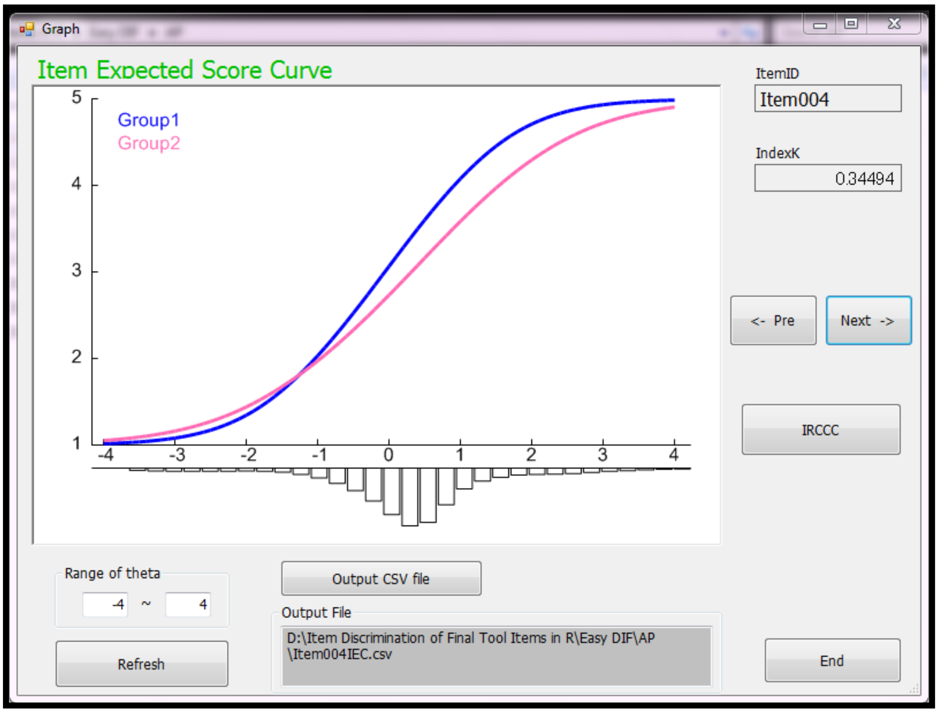


***Figure 4.261*DIF of Academic Procrastination – Item 4**

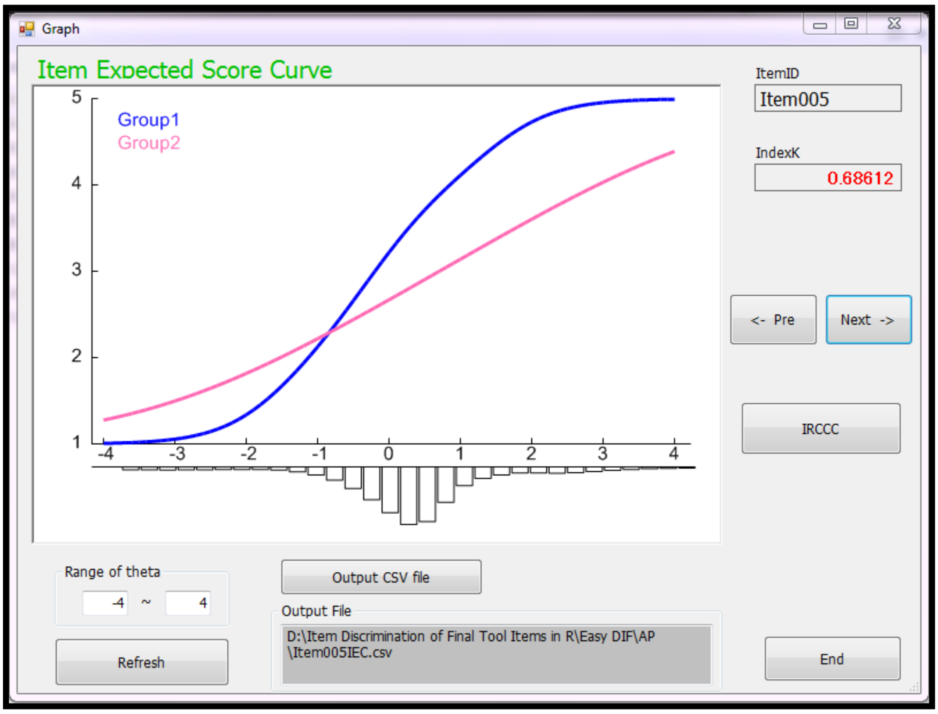


***Figure 4.262*DIF of Academic Procrastination – Item 5**

Interpretation: The above items of academic procrastination variable are part of the AP-SF (2016) scale with five point likert scale responses. Here, the critical K-index is (5-1)*0.1=0.4. Since the generated K-values of first the four items is less than 0.4, desirably these items do not show differential item functioning with respect to gender. The fifth item has the K-index of 0.68612, greater than 0.4 and hence should be excluded from further analysis for displaying DIF.

xi. Future Time Perspective

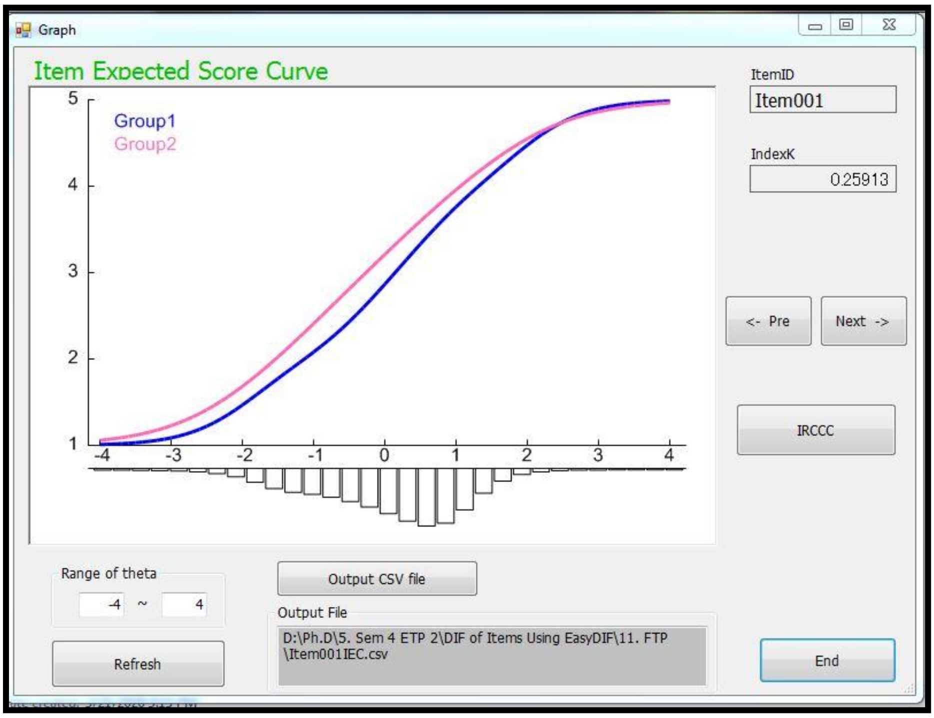


***Figure 4.263*DIF of Future Time Perspective – Item 1**

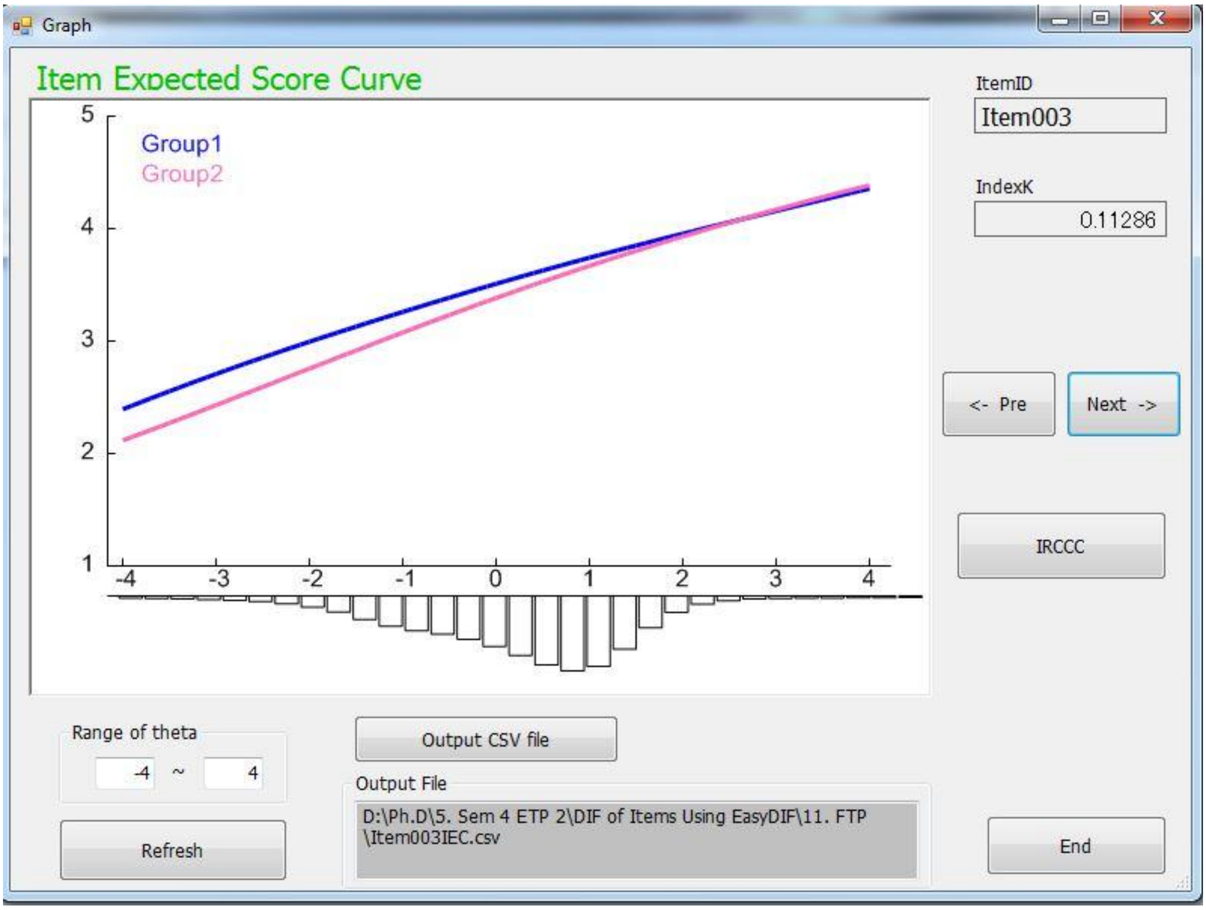


Figure 4.264**DIF of Future Time Perspective – Item 3**

Interpretation: The above items of future time perspective variable are part of the ZTP-SF (2015) scale with five point likert scale responses. Here, the critical K-index is (5-1)*0.1=0.4. Since the generated K-values of first tand third items is less than 0.4, desirably these items do not show differential item functioning with respect to gender. The second item has poor psychometrics that no K-index is generated by the software and hence is excluded from further analysis.

xii. Time and Study Environment:

DIF of Items of Scale 12 – Time and Study Environment:

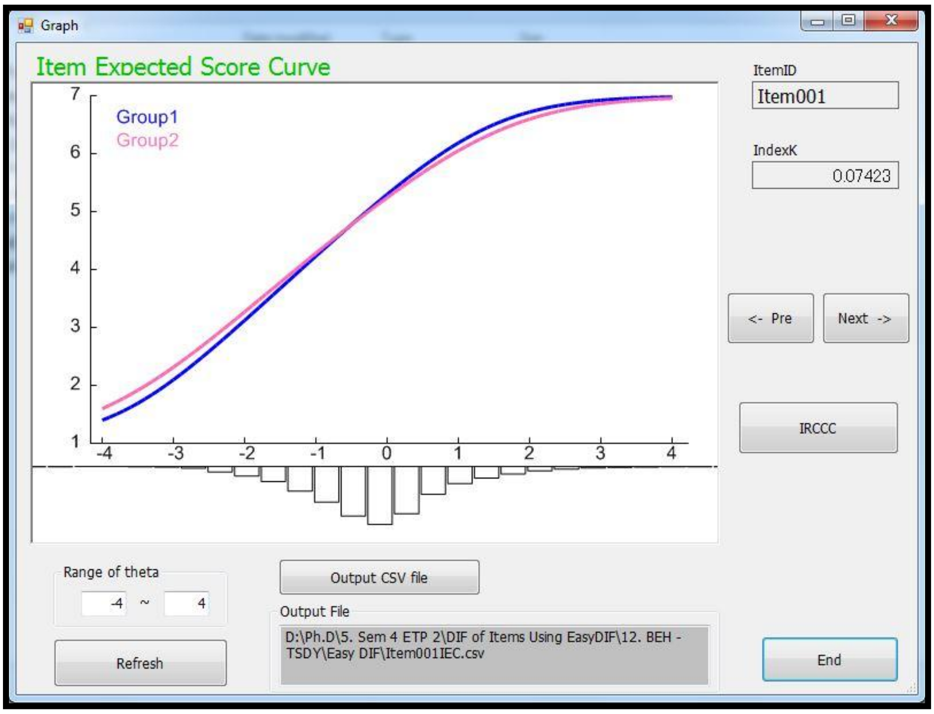


***Figure 4.265*DIF of Time and Study Environment – Item 1**

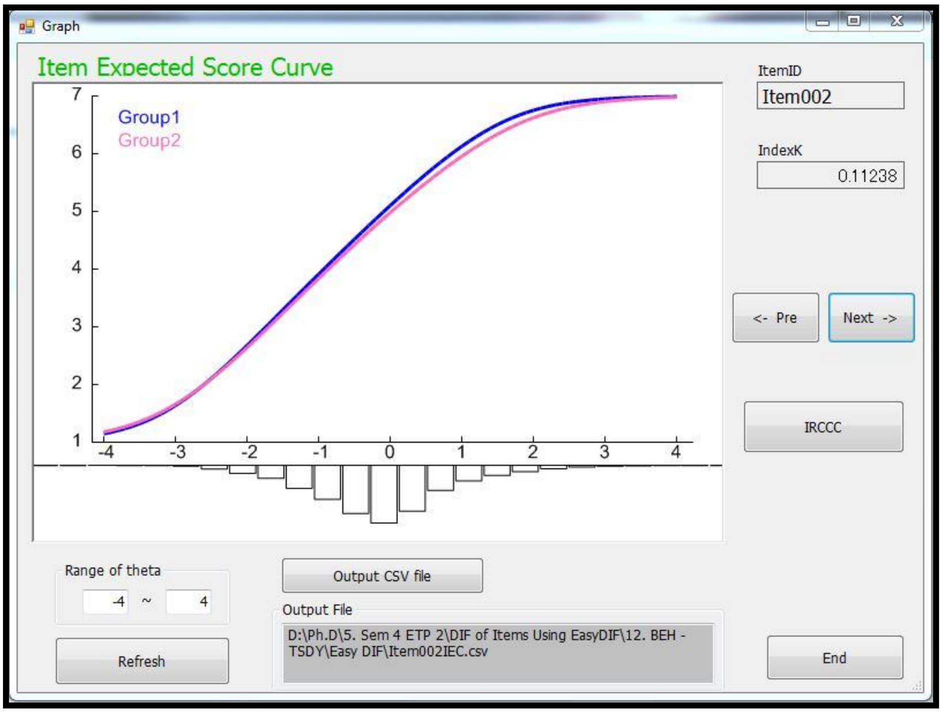


***Figure 4.266*DIF of Time and Study Environment – Item 2**

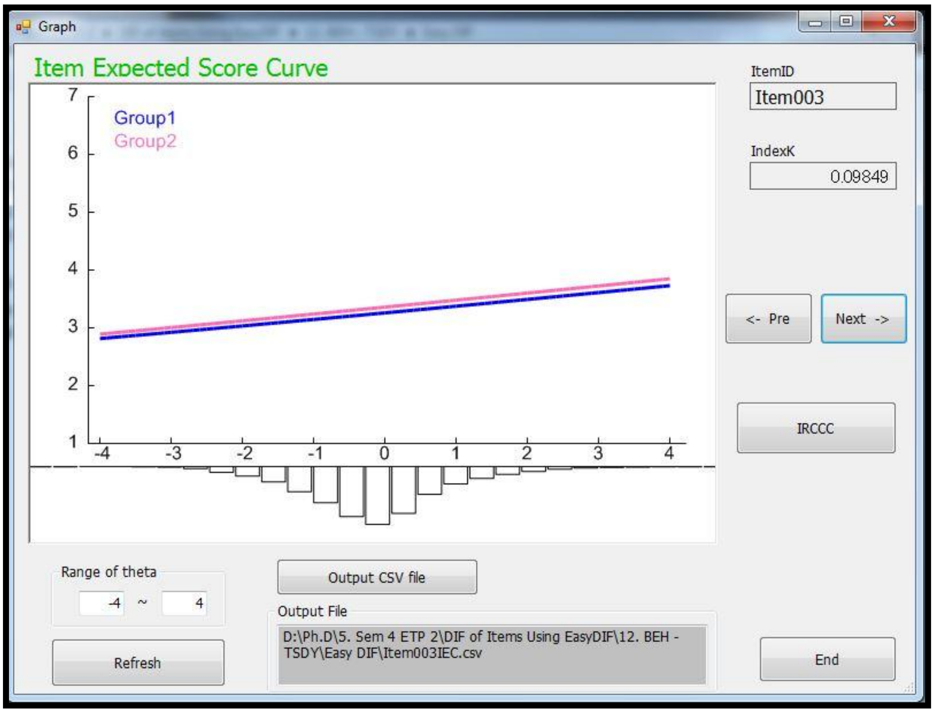


Figure 4.267DIF of Time and Study Environment – Item 3**

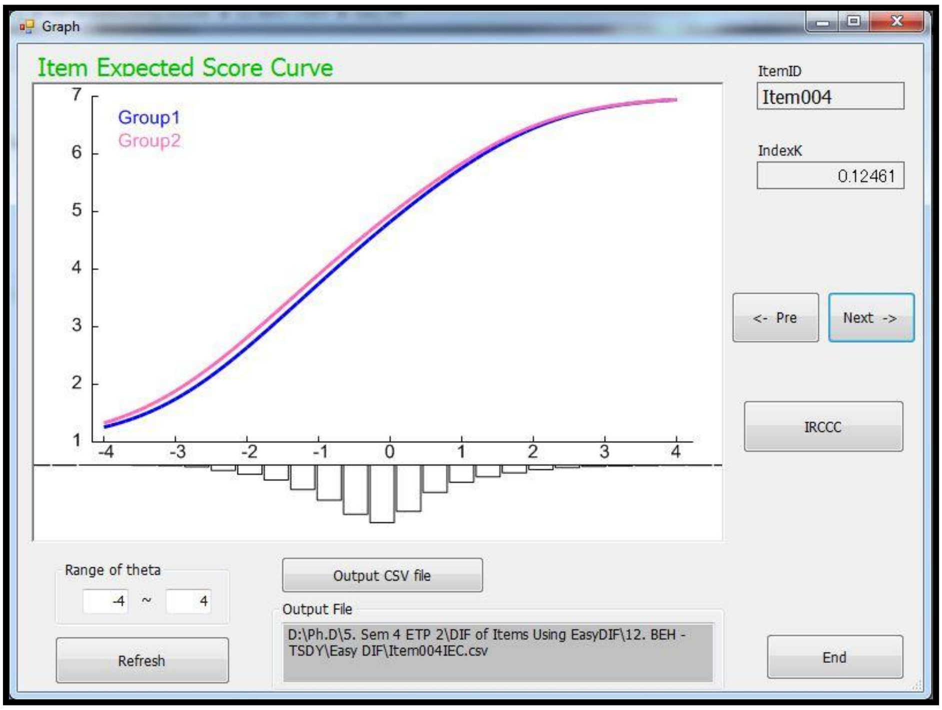


Figure 4.268DIF of Time and Study Environment – Item 4**

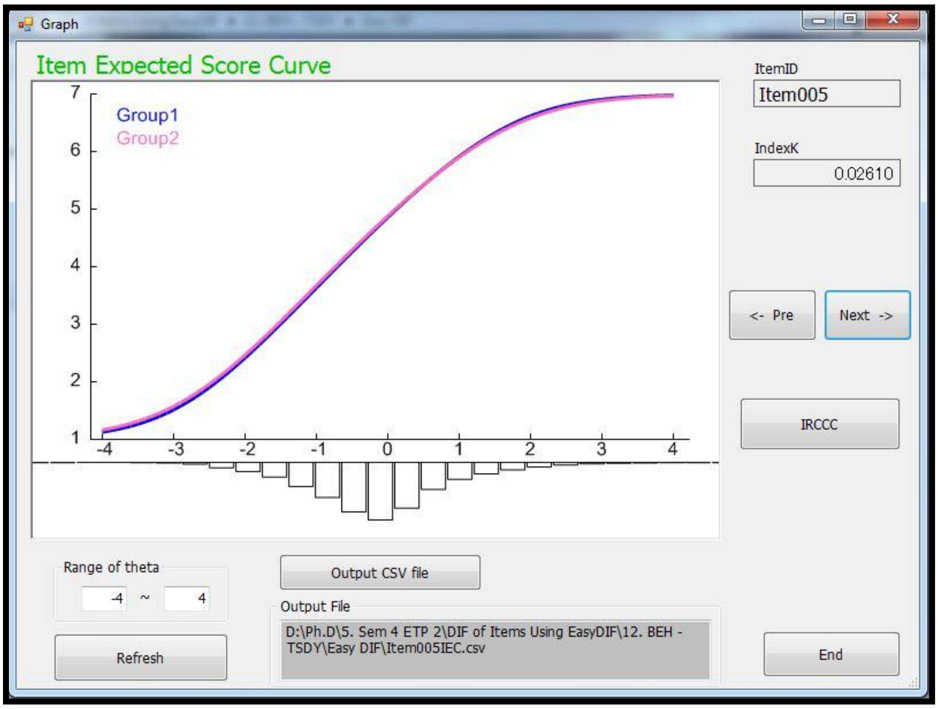


*Figure 4.269*DIF of Time and Study Environment – Item 5

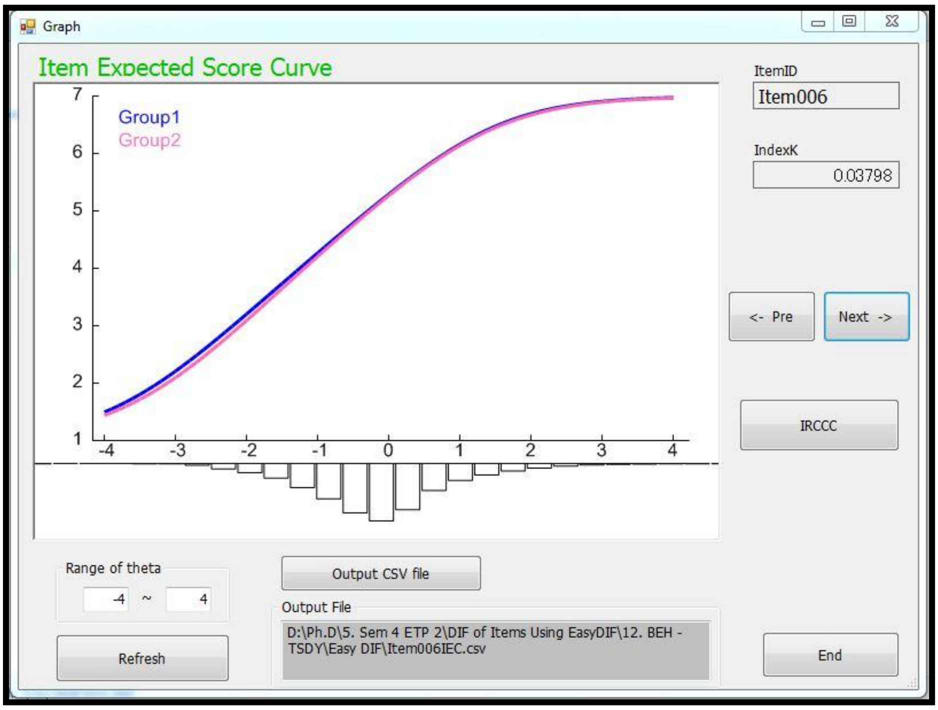


*Figure 4.270*DIF of Time and Study Environment – Item 6

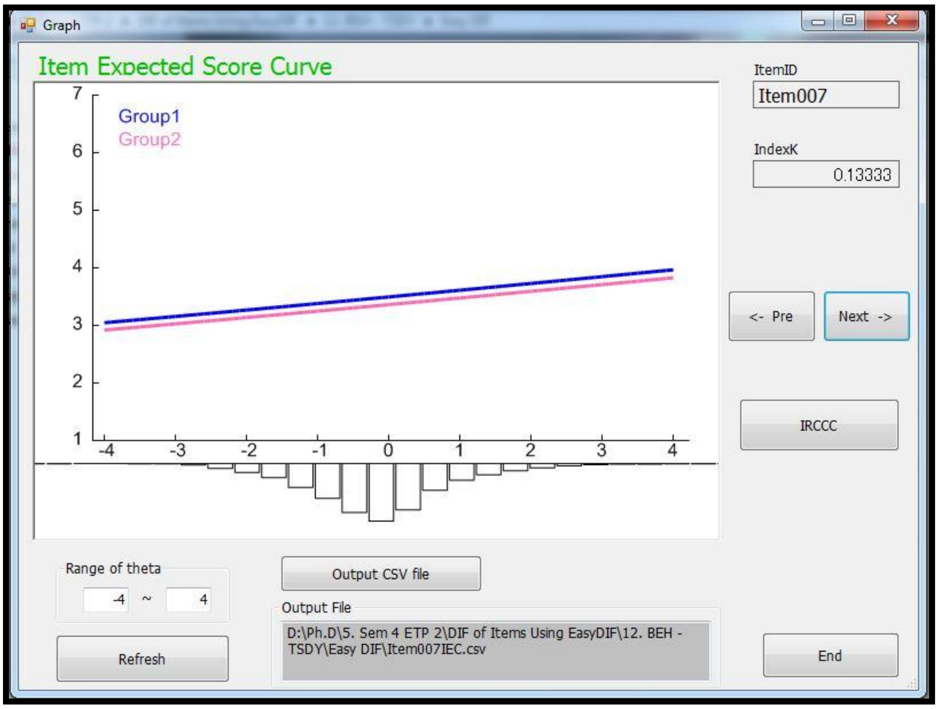


Figure 4.271**DIF of Time and Study Environment – Item 7**

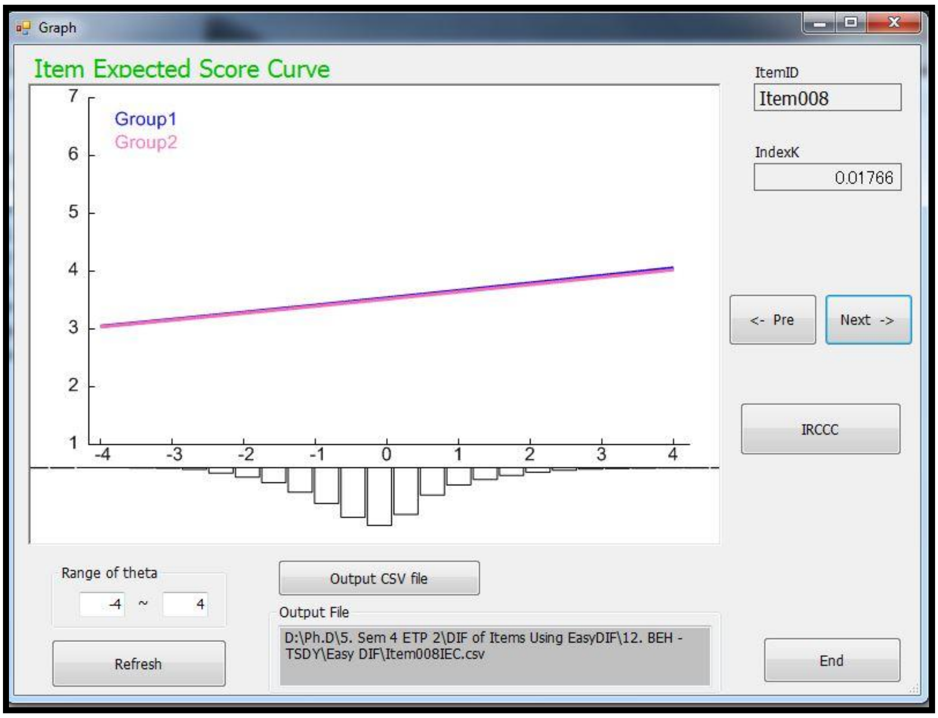


Figure 4.272**DIF of Time and Study Environment – Item 8**

Interpretation: The above items of time and study environment variable are part of the MSLQ (1991) scale with seven point likert scale responses. Here, the critical K-index is (7-1)*0.1=0.6. Since the generated K-values of all the eight items is less than 0.6, desirably none of these items show differential item functioning with respect to gender.

xiii. Reappraisal

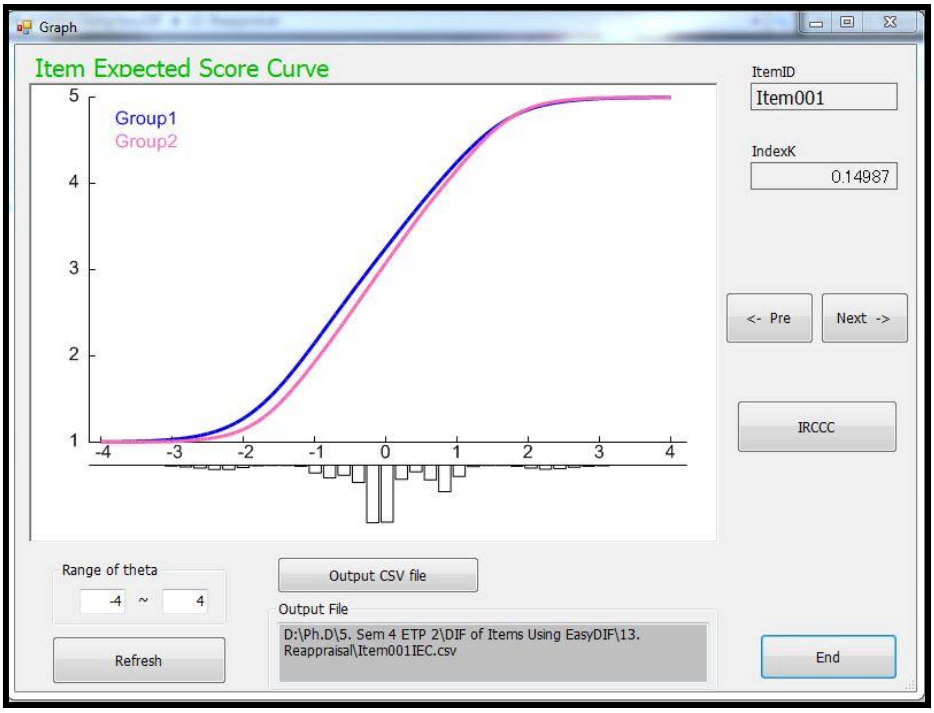


***Figure 4.273*DIF of Reappraisal – Item 1**

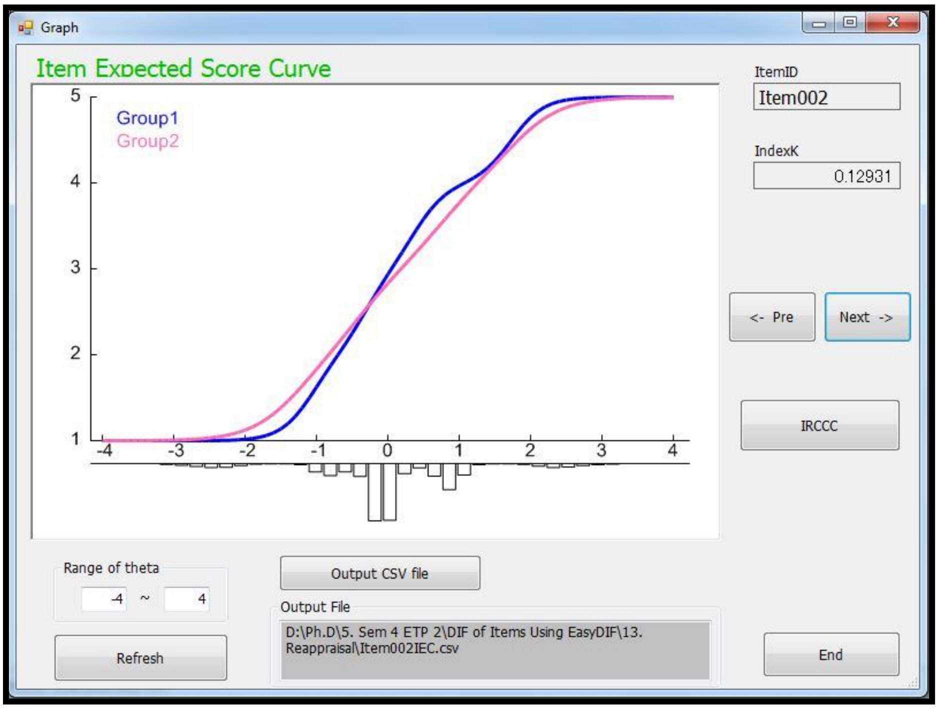


***Figure 4.274*DIF of Reappraisal – Item 2**

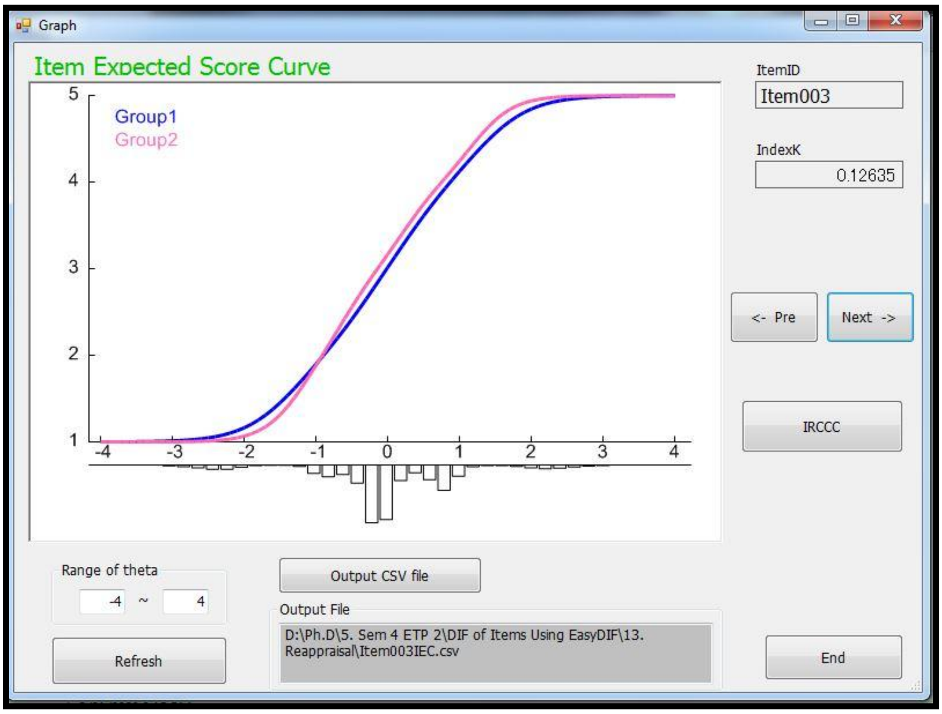


***Figure 4.275*DIF of Reappraisal – Item 3**

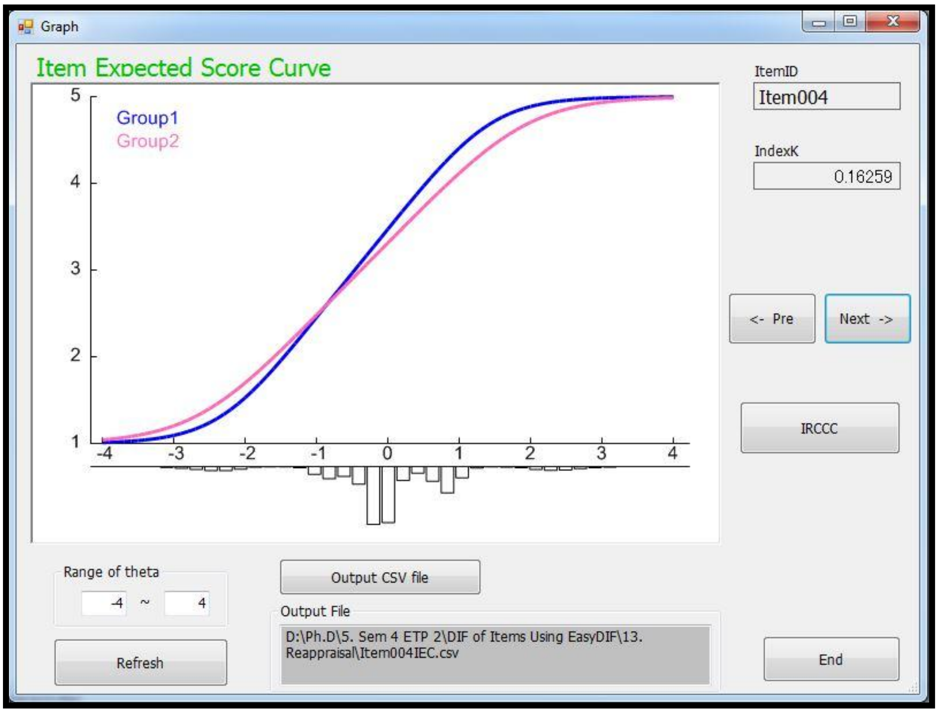


***Figure 4.276*DIF of Reappraisal – Item 4**

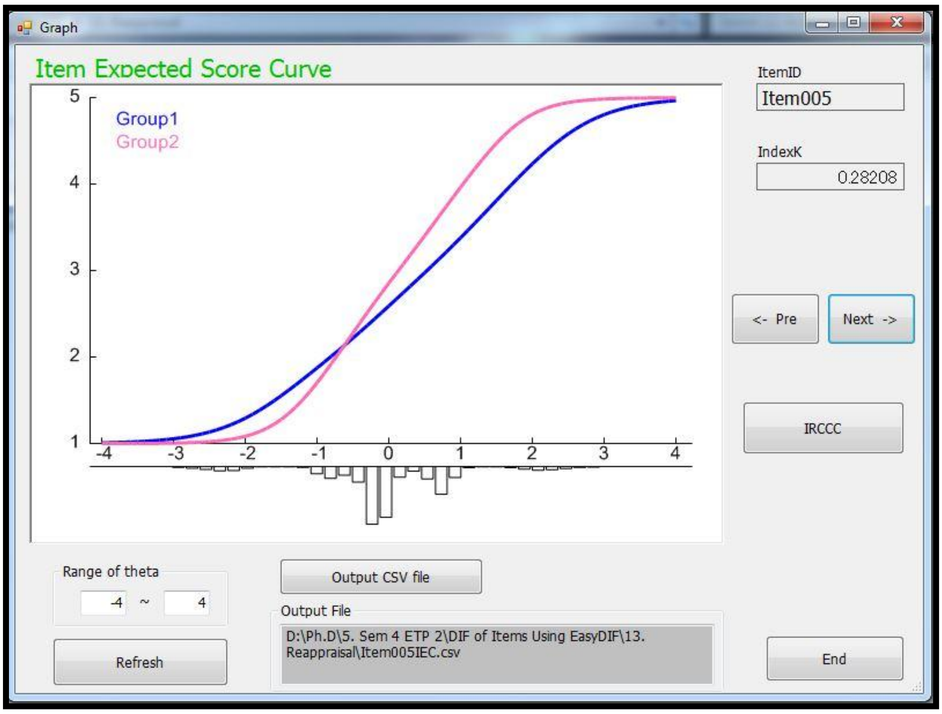


***Figure 4.277*DIF of Reappraisal – Item 5**

Interpretation: The above items of reappraisal variable are part of the AERQ (2016) scale with five point likert scale responses. Here, the critical K-index is (5-1)*0.1=0.4. Since the generated K-values of all the five items is less than 0.4, desirably these items do not show differential item functioning with respect to gender.

xiv. Suppression:

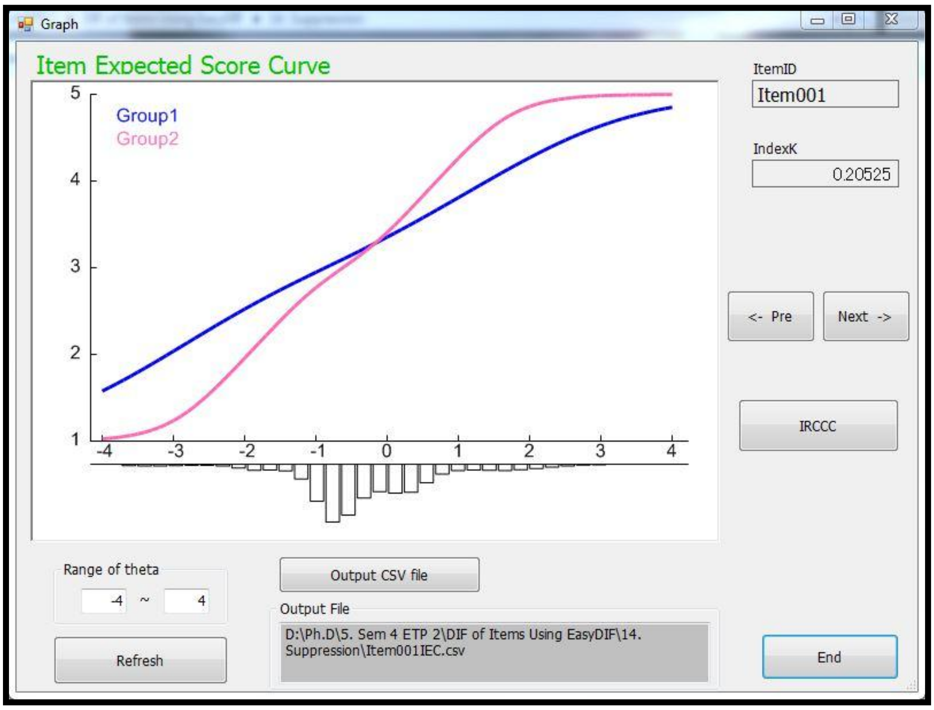


Figure 4.278**DIF of Suppression – Item 1**

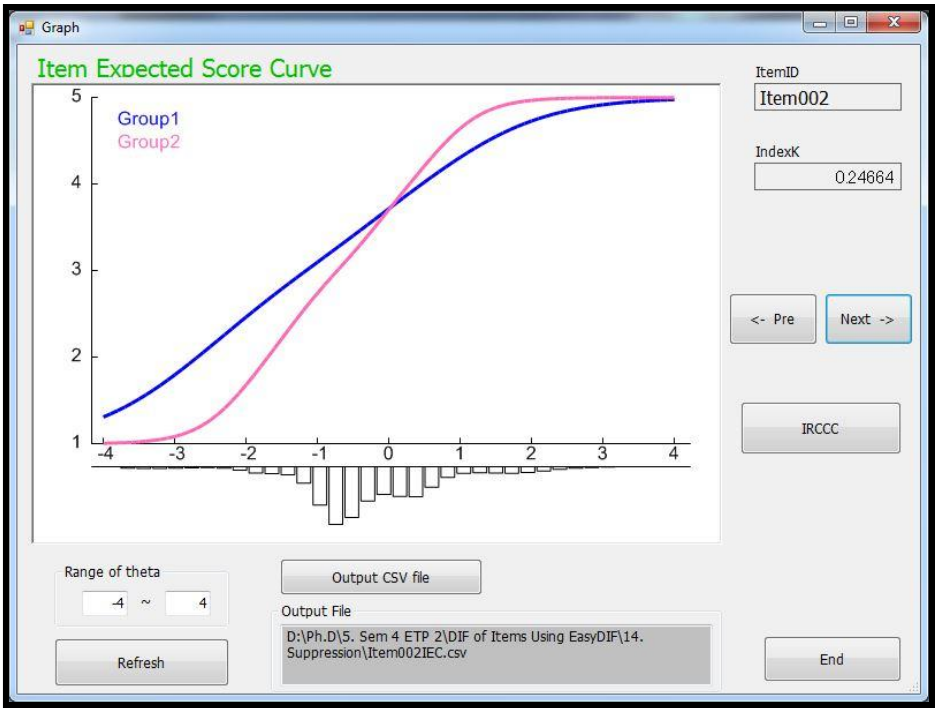


***Figure 4.279*DIF of Suppression – Item 2**

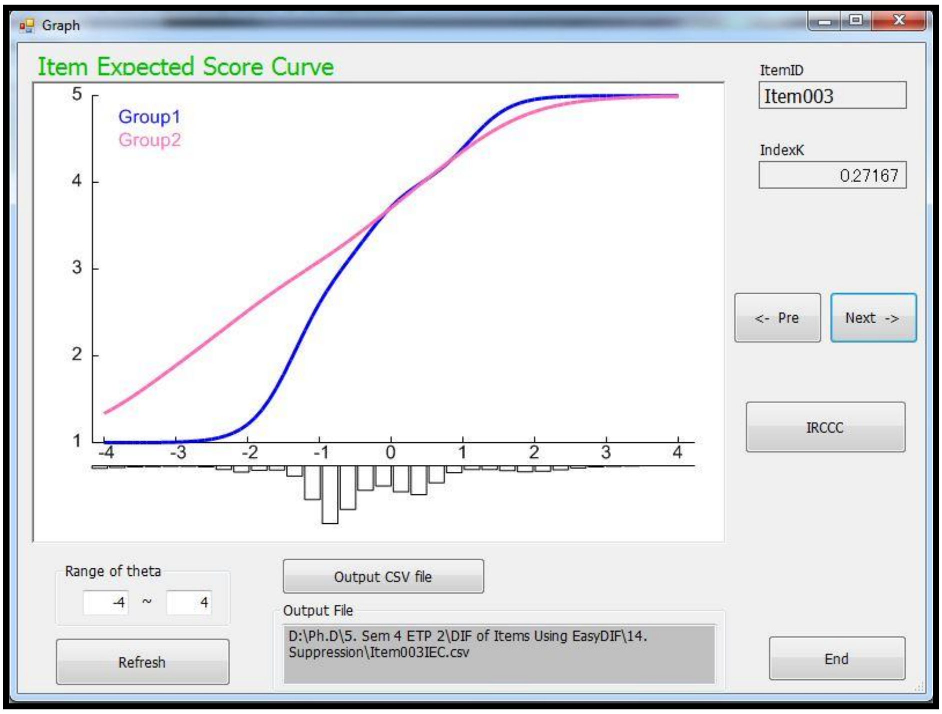


***Figure 4.280*DIF of Suppression – Item 3**

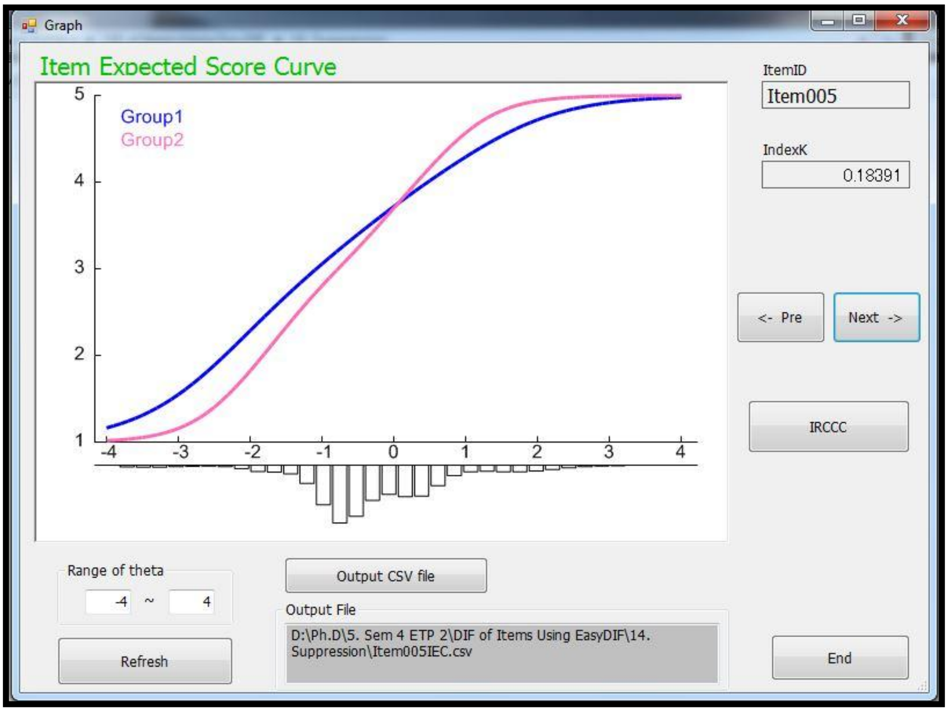


***Figure 4.281*DIF of Suppression – Item 5**

Interpretation: The above items of suppression variable are part of the AERQ (2016) scale with five point likert scale responses. Here, the critical K-index is (5-1)*0.1=0.4. Since the generated K-values of the four out of five items (barring item 4, whose DIF is not generated by the software) is less than 0.4, desirably these items do not show differential item functioning with respect to gender.

4.5 Final Items of the Revised Integrated Trait Model of Self Regulated Learning Questionnaire:

Some of the guidelines followed during the survey design for the preparation of this final tool (Appendix – A) are that the chosen measures in it are all reflective in nature allowing the usage of SPSS AMOS software for model testing. The scale of the variables is proper in the sense, that the number of responses in their tool remains unaltered as in the original scale, except for metacognition awareness inventory. It is originally a dichotomous scale, which cannot be allowed for reflective constructs requiring the reflection of entire measurement continuum and for reliability issues (Krosnick and Presser, 2009), and hence called for re-validation with a five point likert scale. The responses of all the items go from low to high allowing a consistency during data punching and analysis, where a rise in the value of the response means increase in the measured trait. All the 67 continuous items are measured using five or seven point Likert scales (except for academic delay of gratification with four options) required for conducting confirmatory factor analysis and SEM based on the estimator Maximum likelihood ML (Rhemtulla, Brosseau-Liard and Savalei, 2012; Boateng, Neilands, Frongillo, Melgar-Quiñonez, and Young, 2018). There are no reverse coded questions, to surpass the factor analysis issues related to culture. A reverse coded question can be answered positively in one culture and negatively in another, raising split loading of items and confusion in factor determination during factor analysis. The four items of academic procrastination were re-reverse coded questions so that these items in the final scale were in the same direction as in the regular items. Every item measures only one aspect of its variable, without any assumptions made regarding the measured variable. The item qualifies to be asked for the intended sample subjects. No items are sensitive in nature. There are five distractor items intermitently added amidst the other 62 items, belonging to unrelated variables like emotional intelligence and dispositional optimism, in the final tool of total 67 items, to test the sincerity of the respondents while responding the items.

4.6 Estimation of the Polychoric Omega Reliability of the SRL Variables as part of the Pilot Study:

4.6.1 Introduction to Robust and Ordinal Reliability Estimation:

According to the Classical test theory (CTT), reliability is defined as“the ratio between variance in true score T to that of the observed score X” (Raykov and Marcoulides, 2010), by summing the scores of several items (x1, x2, x3, x4) and creating a composite score (shown in Fig.1 and Fig.2). The Cronbach’s alpha (Cronbach and Shavelson, 2004; Cronbach, 1951, 1988) and McDonald’s Omega (McDonald, 1999) are the two most commonly reported estimates of consistency in composite scores.

But, Cronbach’s alpha underestimates the true reliability of a scale, if the assumptions of essentially Tau-equivalence in general are violated (Graham, 2006, Peters, 2014, Sijtsma, 2009). Also, Cronbach’s alpha can be the estimate of reliability, only if the construct is unidimensional (Miller, 1995), there is true score equivalence of the items and their errors (E1, E2, E3 and E4 in Fig.1) do not co-vary and are independent (Raykov, Marcoulides and Patelis, 2015).

In the figure, under the assumption of unidimensionality, the latent variable T solely causes the partial variance in the items x1 to x4, while the unique error terms represented as E1 to E4 are responsible for the remaining variance in each of these items. The composite observed score X (shown in Fig.2) is a total variance in each of the items x1 to x4, along with the variances shared by the items among them.

The underestimation of the reliability of the scale due to the violation of the assumptions of Tau-equivalence is addressed by omega coeficient of reliability (McDonald, 2013). Though, it does not require the undimensionality of the construct, the items must still be true score equivalents here.

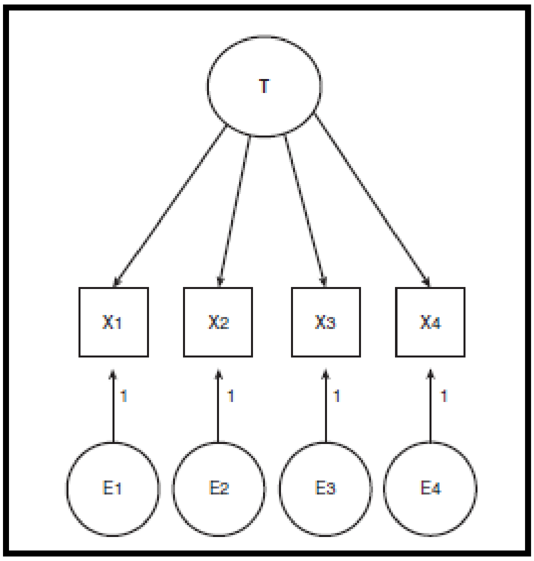


Figure 4.282 **Path Diagram of the Unidimensional Composite True Variable**

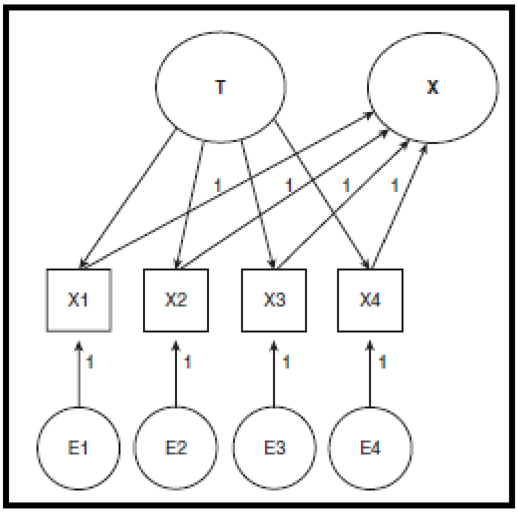


Figure 4.283 **Basic Reliability Path Diagram**

The unidimensionality assumption alone is not enough for the estimation of the composite true score x with precision. Along with this measurement model of essentially Tau equivalence, there are other measurement models like, tau-equivalence model, parallel model, and congeneric measurement model (Lord and Novick, 1968, Feldt and Brennan, 1989) which are useful in estimating psychological construct's reliability.

The discussion on the measurement models associated with classical test theory based reliability estimation begins with the parallel model which is the most strictest measurement model of the composite true score estimation. It calls for unidimensionality and equivalence of the test items. As a result, all the items x1 to x4 here measure the same latent variable, on a same scale, with same preciseness and with same quantity of error ε (Raykov, 1997a, 1997b). When the errors of the test items (E1 to E4) are allowed to vary, the new measurement model is called Tau-equivalent model. When unequal precision of items is added to variance in the error items while measuring the same latent variable, the measurement model is called essentially Tau-equivalent model. Here, the items differ from each otherin measurement of the same latent variable by a unique additive constant α_i, which causes the means of the items to vary. The addition of an additive, changes the mean of the items and keeps the variance unchanged, and hence the reliability unaffected. Because of this aspect, from the perspective of structural equation modeling, the measurement models of tau-equivalence and essential tau-equivalence are both similar. Cronbach's alpha can be the true estimand of reliability of a scale provided the essentially Tau-equivalence condition is satisfied. Otherwise, based on the severity of the violation of the condition, underestimation of the true reliability of a scale can vary from 0.6 to 11 percent (Green and Yang, 2009).

The congeneric model is the least restrictive and popular measurement model of estimating reliability, where the requirements are bare minimum that the scale should be unidimensional and all the items must measure the same construct. The precision of measurement of the latent variable by the items can differ (with the help of an additive constant α_k and a multiplicative constant β_k to each item X_i) and along with their errors ε_i. McDonald's Omega coefficient of reliability is such a congenric estimand of reliability, which is looked upon as the solution for underestimation of reliability by Cronbach's alpha. However, stricter the measurement model, better is the estimation of the scale reliability.

Moreover, the use of the sample covariance matrix during the estimation of these non-robust coefficients of alpha and omega, makes them vulnerable to the presence of outliers under which the obtained estimates prove to be biased (Liu and

Zumbo, 2007; Wilcox, 1992; Sheng and Sheng, 2013; Liu, Wu, and Zumbo, 2010). This issue is addressed by calculating and communicating the confidence interval versions of alpha and omega coefficients (Iacobucci and Duhachek, 2003; Fan and Thompson, 2001; Raykov and Shrout, 2002) along with their standard errors. This is achieved by downweighting the outlier cases through a R-package *Coefficientalpha* (Zhang and Yuan, 2016). It performs tau-equivalence condition and homogeneity of items tests as well under which the null hypothesis of these conditions being satisfied by the items by default is tested by producing a F-statistics based p-value, leading to either the acceptance or rejection of the null hypothesis. It is followed by obtained the robust alpha and omega reliability estimates in the presence of data non-normality and presence of outliers.

Finally, the use of the sample covariance matrix during the estimation of the non-robust coefficients of alpha and omega based on the assumption that the responses of the items, are continuous in nature, is also erraneous. The responses of different psychological Likert scale based instruments are ordinal with categories like 1=Strongly disagree, 2=Disagree, 3=Neutral, 4=Agree and 5=Strongly Disagree. This makes the data ordinal in nature instead of the assumption of being continuous. As a result, a true estimate of the reliability can only be obtained through the estimation of a polychoric correlation matrix instead of the conventional Pearson correlation matrix (Gadermann et al., 2012). Such a correlation matrix can then be used in the estimation of the ordinal versions of alpha (Zumbo, Gadermann, and Zeisser, 2007) and omega (Zinbarg et al. (2005) which are appropriate estimates of reliability when Likert scale based psychological tools are used in data collection. Since, Deng and Chan (2017) showed that omega is a better estimand of reliability than alpha, the polychoric version of omega is calculated for all the fourteen self regulated learning variables in R/RStudio along side their Cronbach's alpha estimated in SPSS Statistics Ver. 23.0 for compare and contrast of the underestimation of scale reliability by the latter. However, Chalmers (2017) presented a different narratitve of Ordinal polychoric reliability as a hypothetical reliability and defined it merely as "estimate of the expected reliability in an alternative reality whereby categorical responses have been replaced by continuous responses".

4.6.2 Steps / R Codes for Evaluating Robust Omega Reliability:

The R/RStudio code / steps for conducting the estimation of the robust forms of alpha and omega preceded by tau-equivalence tests and homogeneity of items tests which are the necessary precursors of such study are:

1. Import the data file in RStudio console using *Import Dataset*.
2. Install the package *Psych*
3. Library *Psych* # for activation of the package#
4. Install the package *GPArotation*.
5. Library *GPArotation*
6. Install *Coefficientalpha*
7. Library *Coefficientalpha*
8. tau.test (Data File name) # for conducting Tau-equivalence and homogeneity of items test#
9. alpha (Data File name) # for estimating the non-robust and confidence interval forms of alpha#
10. Upload the data in a text file in the webpage http://psychstat.org/alpha, to get the standard error associated with robust alpha.
11. Omega (Data File name) # for estimating the total and hierarchical forms of Omega
12. Omega.res<-Omega(Data file name, varphi = 0.1, se = TRUE)
13. Summary (Omega.res, prob=0.95) # for calculating of the robust form of Omega, its S.E and its C.I. form of reliability #

4.6.3 Steps / R Codes for Evaluating Polychoric Ordinal Reliability:

The steps to follow in order to estimate the polychoric correlation matrix based ordinal alpha and ordinal omega in R/RStudio are shown below:

1. Import the data file in RStudio console using *Import Dataset*.
2. Install the package *Psych*
3. Library *Psych* # for activation of the package#
4. Polychoric(datafilename) #Estimate polychoric correlation matrix of the provided data

5. Exampledata<-polychoric(datafilename) #define a data frame
6. Alpha(exampledata$rho) # to estimate ordinal alpha
7. Omega(exampledata$rho) # to estimate ordinal omega
8. Alpha(datafilename) # to estimate Cronbach's alpha
9. Omega(datafilename) # to estimate McDonald's omega

(Or)Use the R package userfriendlyscience (Peters, 2018) to generate interval scale Cronbach's alpha, greatest lower bound reliability and ordinal scale point and confidence interval based Polychoric ordinal alpha and polychoric ordinal omega.

1. Import the datafile in R.
2. Install the package "userfriendlyscience"
3. Library (userfrinedlyscience)
4. Scale Reliability (datafile).

4.6.4 Polychoric Ordinal Omega Reliability Estimates of Self Regulated Learning Variables:

Table 4.142 Comparison of Polychoric Ordinal Omega and Cronbach's Alpha of SRL Variables:

S.No.	SRL Variable	Items	Polychoric Omega in R	Cronbach's Alpha in SPSS
1.	Critical Thinking	M47, M51, M66, M71	0.74	0.706
2.	Organization	M32, M42, M49, M63	0.76	0.687
3.	Planning	P2, P3, P5	0.81	0.817
4.	Self Recording	P10, P11, P12, P14	0.8	0.787
5.	Self Evaluation	P15, P16, P18, P20	0.85	0.826
6.	Goal Orientation	M1, M16, M22, M24	0.73	0.67
7.	Self Efficacy	M12, M15, M20. M21, M31	0.85	0.808
8.	Academic Intrinsic Motivation	AIM8, AIM9, AIM10, AIM15. AIM16, AIM17, AIM22, AIM24	0.87	0.814
9.	Future Time Perspective	ZTP12, ZTP13, ZTP14	0.62	0.565
10.	Academic Delay of Gratification	ADG4, ADG5, ADG8, ADG9, ADG10	0.81	0.692
11.	Academic Procrastination	AP1, AP2, AP3, AP4	0.76	0.667
12.	Time and Study Environment	M35, M43, M65, M70	0.73	0.669
13.	Reappraisal	Reapp1, Reapp2, Reapp3, Reapp4, Reapp5	0.82	0.741
14.	Suppression	Supp1, Supp2, Supp3, Supp4, Supp5	0.77	0.675

Conclusion: The polychoric omega reliability coefficient (Gadderman, 2012) for all the fourteen self regulated learning variable is greater than the acceptable limit of 0.6 for psychological variables (Kline, 1999). The under estimation of the vital estimate by the notorious Cronbach's alpha (1951) is also presented for compare and contrast.

4.7 List of Region-wise Institutions visited for Final Data Collection:

The final data collection was conducted using Face-to-Face method and online method. In the Face-to-face method, the respondents are distributed a questionnaire in any appropriate place like in the classroom, home or in the workplace (Collis and Hussey, 2014). It is time-consuming, but the response rate is high, and allows the data collection to be done in a highly comprehensive manner (Collis and Hussey, 2014). Face-to-face was coupled with online distribution in this research tool during COVID-19 epidemic, in order to further rise the chance of reaching the optimum sample size, through more accurate screening.

As part of online method, web-tools like Freeonlinesurveys, SurveyMonkey, and Google Form are available for creating and distributing a survey to the subjects of the study by using social media or email (Collis and Hussey, 2014). When all the responses are gathered, the data file can directly be exported to programs such as SPSS Statistics software, Microsoft Excel, or other statistical software tools (Collis and Hussey, 2014). In this research, Google Forms was used to create the survey and WhatsApp was used to distribute it. Both platforms were chosen owing to their free of charge availability, easy-to-use, easy accessibility, wide spread usage and convenience. These platforms allowed the researcher to gather data from subjects of required number of engineering institutions located in Majha, Doaba and Malwa regions of Punjab.

The total sample size of the collected data using questionnaire and Google form is 557 from 10 engineering institutions of Punjab, which is one more than the 9 institutions to visit as per the sample design.

There were 53 subjects who did not fill the questionnaire as per the instructions provided. 16 subjects were found to be outliers as per the estimated Mahalanobis distance for multivariate SEM studies, making the total number of outliers in the study to be **69**. Removing these two types of outliers, 488 subjects (557-69), comprised the final sample size of the study.

Table 4.143List of Region-wise Institutions visited for Final Data Collection

S.No.	Name of the Institution	Region	Final Sample Size N=488	Break-up of the Data Collected Per Institution					
				Gender		Batch		Stream	
				M	F	IInd	IIIrd	Comp	Mech
1.	Guru Nanak Dev University, Amritsar	Majha	96	63	33	60	36	62	34
2.	Beant College of Engineering and Technology, Gurdaspur	Majha	109	85	24	57	52	80	29
3.	DAV University, Jalandhar	Doaba	100	64	36	66	34	74	26
4.	Sant Baba Bhag Singh University, Jalandhar	Doaba	35	26	9	14	21	15	20
5.	Ramgarhia Institution of Engineering and Technology, Phagwara	Doaba	14	10	4	7	7	12	2
6.	Lala Lajpat Rai Institute of Engineering and Technology, Moga	Malwa	35	20	15	17	18	30	5
7.	CT University, Ludhiana	Malwa	12	4	8	0	12	12	0
8.	Thaper Institute of Engineering and Technology, Patiala	Malwa	20	19	1	9	11	5	15
9.	Punjabi University, Patiala	Malwa	9	9	0	9	0	0	9
10.	Shaheed Bhagat Singh State Technical Campus, Ferozepur	Malwa	58	51	7	25	33	32	26

4.8 Outlier Detection through Mahalonobis Distance Estimate of the Final Data:

In order to detect the outliers among the multivariate 14 variables of self regulated learning, the Mahalonobis distance of the data rows is calculated in SPSS Statistics Ver.23.0, under the tab Analyze>Regression>Linear. The independent variables comprise of the 14 self regulated learning strategies variables from the five components of the construct. The dependent variable can be any arbitrary variable, say Gender. Click Mahalonobis distance check box under Save option and click OK. The distances are calculated and are visible in the data view. Sort the rows using descending values. The calculated distances are compared to Chi-square distribution for the same degrees of freedom which is equal to the number of independent variables in the study. For this, click Tab Transform>Compute Variable. Define a variable probability_MD and use the numeric expression 1-CDFChi.Sq(Mahalonobis distance parameter, degree of freedom). Click OK. The probability is calculated, visible in the data view and extend the values up to five decimals and compare these values with 0.001. Probability values less than 0.001 are termed outliers. Define a variable outlier and use the expression probability values<0.001 to obtain the records which are outliers marked as 1 in the data view. Delete these rows to obtain the data set free from multivariate outliers. The final sample size was 557. Post Mahalonobis distance calculation and removal of 16 such outliers along with the removal of 53 unfilled questionnaires, the sample size was 488.

4.9 Reliability Analysis of the Self Regulated Learning Variables in R/RStudio:

In most of the social sciences measurements, though the instruments have Likert scales to register the responses in ordinal manner, the data is treated as continuous as if arising from an interval scale (Olsson, 1979). This assumption further leads to severe underestimation of the reliability of any instrument.

According to Gadermann et al. (2012), the extent to which the Cronbach's alpha (Cronbach, 1951) underestimates the theoretical reliability when the response data is assumed continuous while it is ordinal in nature or the extent of accurate estimation of the theoretical reliability by the ordinal alpha (Zumba et al., 2007) in the mentioned scenario is quantitatively estimated by the estimand "attenuation index" given by the formula:

Percent attenuation = [100*(alpha-theoretical reliability)/theoretical reliability)]. The alpha in this equation can be either Cronbach's alpha or polychoric alpha.When either of them are closer to the theoretical reliability, the attenuation is closer to zero. The more the deviation is between alpha and theoretical reliability, the closer the value will be to -100 which is the maximum possible extent of attenuation. For example, if the raw Cronbach's alpha is 0.46 and the ordinal alpha is 0.85, then, the attenuation index as estimated by the above formula is -46, which represents the extent of underestimation by Cronbach's alpha of the theoretical reliability. The ordinal alpha is an apt and unbiased estimand of the theoretical reliability irrespective of the skewness of the scale point distributions, the number of scale points and the magnitude of the theoretical reliability, where the accuracy of Cronbach's alpha decreases. Though conceptually, ordinal and Cronbach's alpha are same, the vital difference is that while the former is based on polychoric correlation meant for calculating the correlation matrix for ordinal data, the latter is based on Pearson's product moment correlation which is used in the estimation of the correlation matrix when the data is continuous.

Table 4.144Reliability Analysis of SRL Scales Involving Cronbach's Alpha, Greatest Lower Bound Reliability, Polychoric Omega, Polychoric Alpha and Attenuation Index:

S.No.	SRL Variable	Items (n=488)	Cronbach's Alpha	GLB	Polychoric Ordinal Alpha – C.I. / Point	Polychoric Ordinal Omega	Attenuation Index
1.	Critical Thinking	M47, M51, M66, M71	0.78	0.81	(0.79,0.84) / 0.82	(0.79,0.85)	5 %
2.	Organization	M32, M42, M49, M63	0.78	0.79	(0.8,0.85) / 0.82	(0.8,0.85)	5 %
3.	Planning	P2, P3, P5	0.76	0.76	(0.78,0.84) / 0.81	(0.78,0.84)	6.1 %
4.	Self Recording	P10, P11, P12, P14	0.72	0.73	(0.75,0.81) / 0.78	(0.75,0.81) / 0.78	7.67 %
5.	Self Evaluation	P15, P16, P18, P20	0.77	0.78	(0.78,0.84) / 0.81	(0.78,0.84)	5 %
6.	Goal Orientation	M1, M16, M22, M24	0.73	0.77	(0.74,0.81) / 0.77	(0.74,0.81)	5.19 %
7.	Self Efficacy	M12, M20, M21, M31	0.82	0.85	(0.83,0.87) / 0.85	(0.83,0.88) / 0.85	3.53 %
8.	Academic Intrinsic Motivation	AIM8, AIM9, AIM10, AIM15. AIM16, AIM17, AIM22, AIM24	0.83	0.88	(0.84,0.87) / 0.86	(0.84,0.88) / 0.86	3.48 %
9.	Future Time Perspective	ZTP12, ZTP13, ZTP14	0.48	0.52	(0.46,0.61) / 0.54	(0.49,0.62) / 0.54	**11.11 %**
10.	Academic Delay of Gratification	ADG4, ADG8, ADG10	0.48	0.47	(0.52,0.65) / 0.58	(0.52,0.65) / 0.58	**17.24 %**
11.	Academic Procrastination	AP1, AP2, AP3, AP4	0.65	0.69	(0.67,0.75) / 0.71	(0.68,0.76)	8.45 %
12.	Time and Study Environment	M35, M43, M65, M70	0.72	0.75	(0.73,0.8) / 0.76	(0.74,0.8)	5.26 %
13.	Reappraisal	Reapp1,	0.63	0.66	(0.63,0.72) / 0.68	(0.64,0.73)	7.35 %

		Reapp2, Reapp3, Reapp4, Reapp5					
14.	Suppression	Supp1, Supp2, Supp3, Supp4, Supp5	0.51	0.6	(0.51,0.63) / 0.57	(0.52,0.64)	**10. 52 %**

Conclusion: All the estimates of four types of interval and ordinal, point and confidence interval reliability were generated using the R package "userfriendlyscience" (Peters, 2018). The ordinal confidence interval reliability coefficient for all the fourteen self regulated learning variables includes the acceptable limit of 0.6 for psychological variables (Kline, 1999). The under estimation of the vital estimate by the notorious interval scale Cronbach's alpha (1951) is also presented for compare and contrast. The attenuation index of the variables academic delay of gratification, future time perspective and suppression are noticeable. The actual ordinal scale based estimate of the reliability of the fourteen variables lies in the mentioned confidence interval, which includes the threshold value of 0.6, implying acceptable reliability for the SRL variables.

4.10 Descriptive Statistics of the SRL Variables:

4.10.1 Measures of Central Tendency and Dispersion –

Table 4.145 Summary of SRL Variables Mean and Standard Deviation

	N	Mean	Std. Deviation
	Statistic	Statistic	Statistic
ADG	488	3.4706	.61024
AP	488	2.8607	1.00770
FTP	488	3.5799	.67954
Reapp	488	3.1598	.78843
Supp	488	3.4910	.63576
AIM	488	4.9834	1.21718
SE	488	5.3750	1.09612
GO	488	5.2587	1.02562
TSDY	488	4.9969	1.08624
CT	488	5.1619	1.04674
ORG	488	5.3227	1.10340

Planning	488	5.4679	1.09522
Srec	488	5.2290	1.02394
Seval	488	5.4180	1.06063
Valid N (listwise)	488		

4.10.2 Measure of Relationship

Table 4.146 SRL Variables Pearson's Product Moment Correlation:

r =	ADG	AP	FTP	Reapp	Supp	AIM	SE	GO	TSDY	CT	ORG	Plan	Srec	Seval
ADG	1													
AP	.316**	1												
FTP	.213**	-.355**	1											
Reapp	-.132**	.136**	.025	1										
Supp	.147**	-.044	.166**	.218**	1									
AIM	/254**	-.287**	.265**	-.007**	.206**	1								
SE	.221**	-.289**	.406**	.046	.244**	.41**	1							
GO	.229**	-.241**	.323**	.125	.25**	.379**	.671**	1						
TSDY	.221**	-.312**	.321**	.091*	.177**	.387**	.592**	.492**	1					
CT	.234**	-.304**	.359**	.127**	.177**	.337**	.635**	.668**	0.6**	1				
ORG	.264**	-.332**	.375**	.001	.201**	.436**	.623**	.5**	.59**	.609**	1			
Plan	.2**	-.245**	.322**	.057	.25**	.352**	.572**	.470**	.541**	.611**	.676**	1		
Srec	.108*	-.237**	.359**	.176**	.219**	.366**	.6**	.535**	.569**	.65**	0.636**	0.633**	1	
Seval	.156**	-.243**	.334**	.132**	.265**	.341**	.572**	.469**	.461**	.571**	.585**	.573**	.658**	1

** - Correlation is significant at the 0.01 level (2 tailed)

*- Correlation is significant at the 0.05 level (2 tailed)

4.11 Comparison of the Alternate Models for Determining the Position of Volition in the Comprehensive SRL Model using SPSS AMOS Ver.23.0 – Objective 3:

A comparison of the two proposed models of SRL, to find the place of volition, is done below:

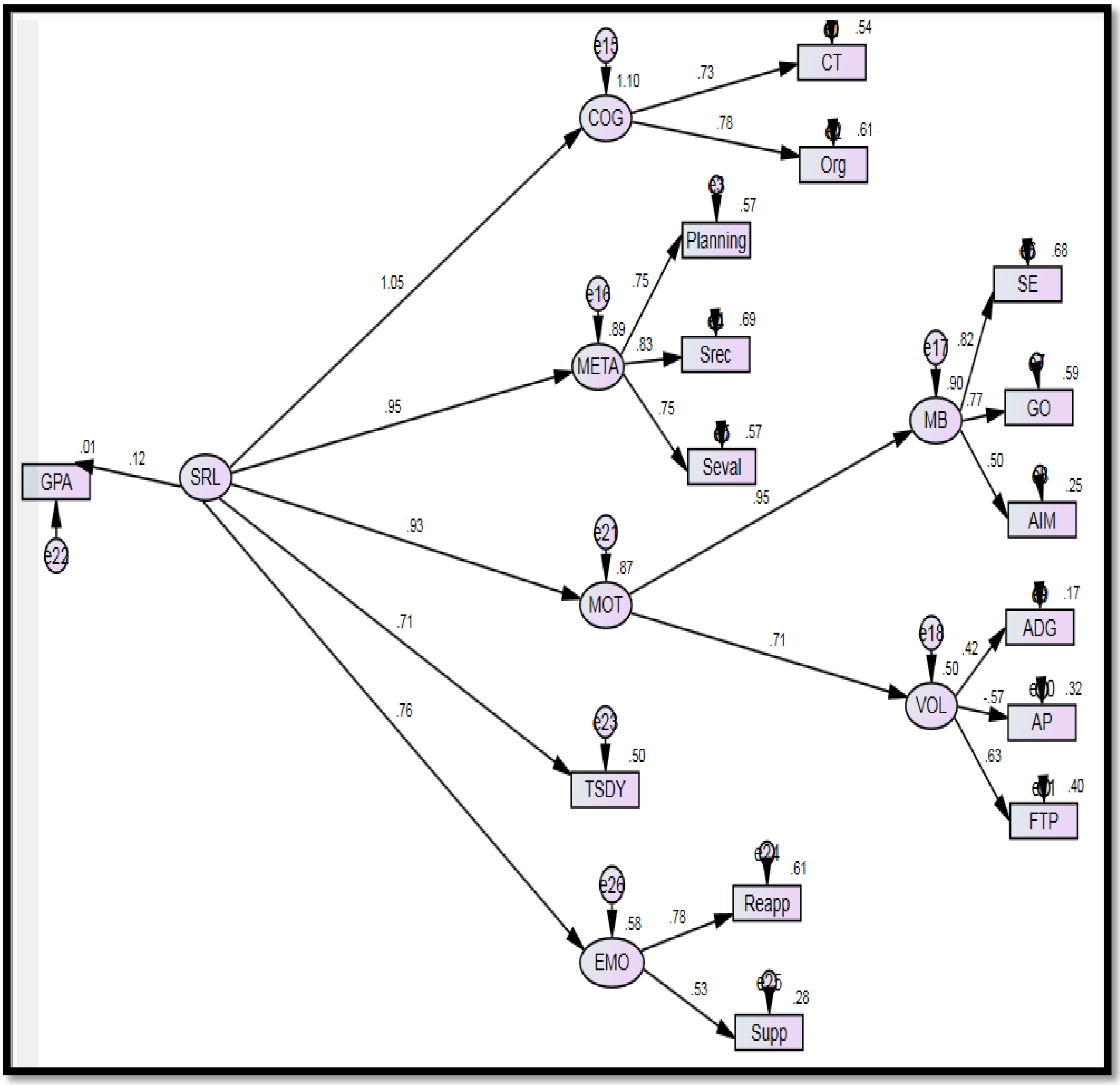


Figure 4.284 **Factor Structure of the role of trait volition in the revised integrative trait model of self regulated learning in the Indian context:Model 1**

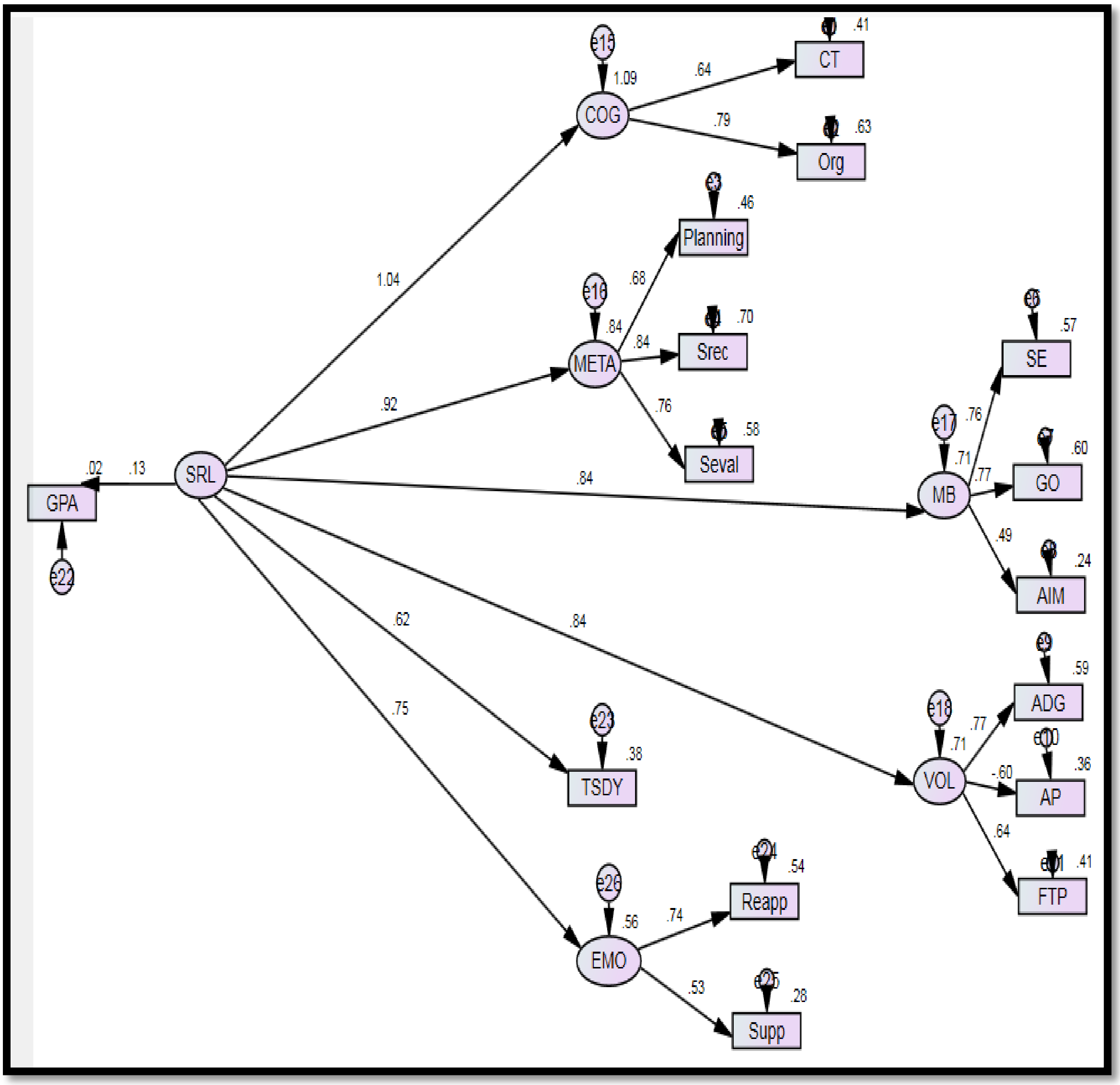


Figure 4.285 **Factor Structure of the role of trait volition in the revised integrative trait model of self regulated learning in the Indian context : Model 2**

4.11.1 Goodness of Fit Estimates of Model 1 and Model 2:

Table 4.147 Estimates of Goodness of Fit:

Estimates	“SRMR”	“TLI”	“CFI”	“RMSEA”	BIC	AIC
Model 1 Magnitude	0.1177	0.811	0.842	0.104	747.857	613.767
Model 2 Magnitude	0.1441	0.703	0.745	0.13	1017.375	891.66

Interpretation: Because the objective 3 was to examine whether volition—as conceptualized —is a fourth factor of SRL (model 2) or is a part of motivation in addition to motivational beliefs (model 1), we compared two models. In order to test the relation of the revised integrative SRL model with academic achievement to establish criterion validity, we included CGPA of the engineering students as a manifest variable into the structural model. SRL predicts AA through GPA, weakly but highly significantly (R=0.126***, p=0.008) providing construct validity to the model. The above table shows the fit-indices of both models, indicating that the model with volition as a subcomponent of motivation fits the data more adequately (model 1). As the model alternatives were constructed based on theoretical assumptions, the estimand Bayesian information criterion (BIC) along with AIC is used to compare the two models (Burnham and Anderson, 2004). Model 1 has the lower BIC value and AIC values and therefore seems more appropriate to model the data (Geiser, 2011), both fit and complexity of the model-wise (van de Schoot and Joop Hox, 2012). This finding is in line with the result of the latest trait SRL model of Dorrenbacher and Perels (2017). *Hence, objective 3 is achieved.*

4.12 Validation of the Revised Integrative Trait Model of Self Regulated Learning among Engineering Undergraduates – Objective 4:

The validation of the revised integrative trait model of SRL is done below:

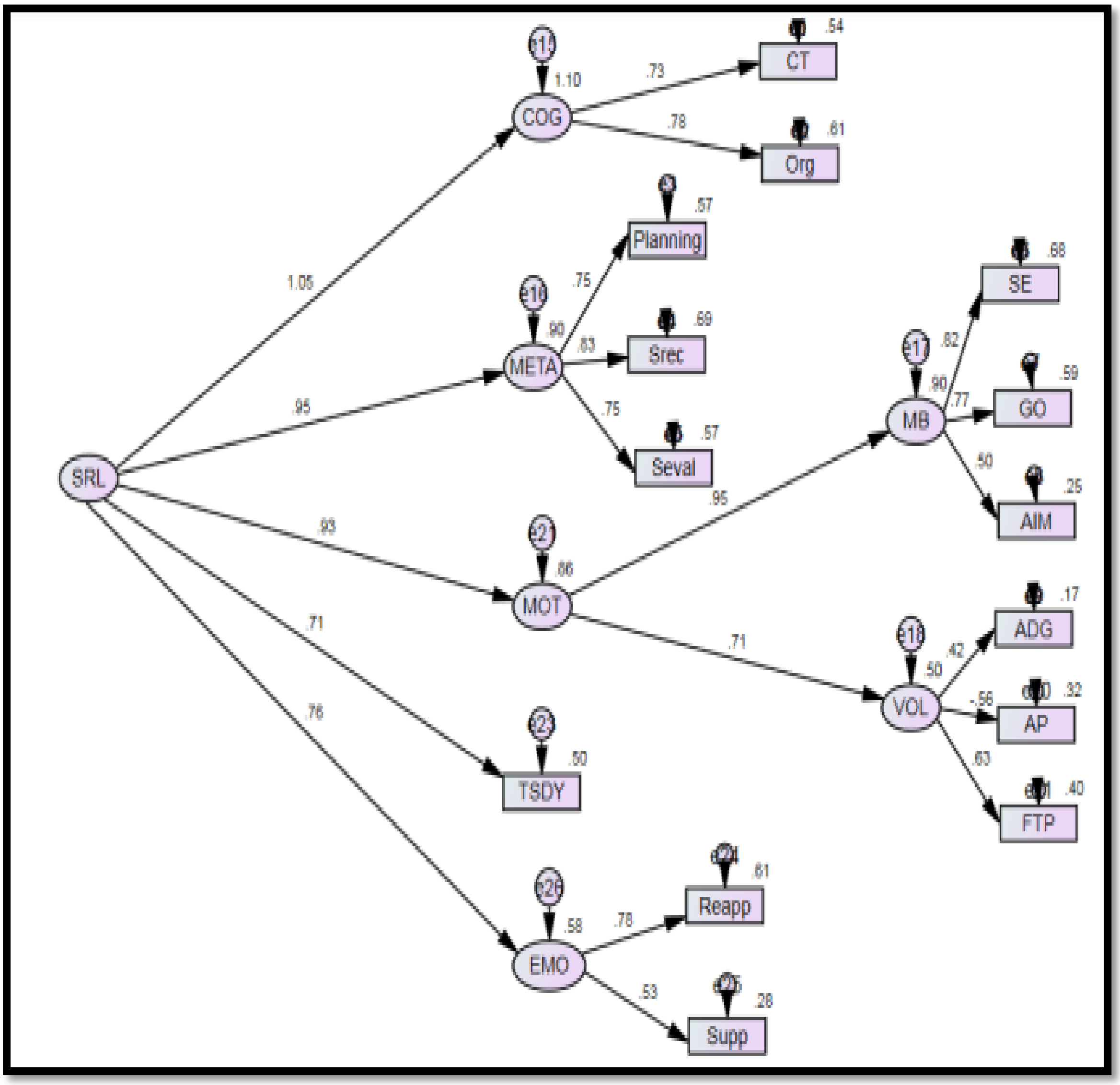


Figure 4.286 **Factor Structure of the revised integrative trait model of self regulated learning in the Indian context**

4.12.1 Goodness of Fit Estimates of the Revised Integrative Trait Model:

Table 4.148 Estimates of Goodness of Fit of the Revised Integrative Model:

Estimates	**"SRMR"**	**"TLI"**	**"CFI"**	**"RMSEA"**	**Remark**
Unconstrained SRL Model	0.1237	0.813	0.846	0.11	***Moderate Fit***

Interpretation: According to Cheung and Rensvold (2002), as the number of items per factor and the number of factors in a model increase, all the goodness of fit indices except RMSEA get affected. ***As the model's complexity increases, its goodness of fit estimands have smaller values (Kenny and McCoach, 2003; Ruch et al., 2018).*** It is because in confirmatory factor analysis and structural equation modeling, small and theoretically non-important factor loadings and correlated error terms are reduced to zero as a hypothesis, in the model (Hall, Snell and Foust, 1999; Hu and Bentler, 1998), resulting in a negative impact on the overall goodness of fit. They also warned the research community not to ignore the aspect of model complexity while judging the model fitness based on certain rule of thumb like CFI to be equal to 0.9.

Buric et al. (2016) specifically mentioned that conventional fit indices like TLI and CFI are often too restrictive when employing the CFA to test the underlying structure of multidimensional measures comprising 5 to 10 factors each represented by 5 to 10 items (Marsh, Hau, and Wen, 2004).

The present goodness of fit estimates are acceptable since according to Naor et al. (2008), CFI and TLI above 0.8 make the model acceptable with moderate fit, is supported by Bentler (1990), Bentler and Bonett (1980), Baumgartner and Homburg(1996), Doll, Xia and Torkzadeh (1994), Cheng (2011) and Sharma et al. (2005). The RMSEA value lying between 0.8 and 1 is treated to be adequate fit as per the works of Browne and Cudeck (1993) and Kenny et al. (2014).

In order to study the relationship model complexity and goodness of fit have with sample size, data of 45 more students from one of the sample institutions (Thaper Institute of Engineering and Technology, Patiala), consisting of 23 girls and 22 boys, 25 second years and 20 third year students and 22 computer science and 23 mechanical engineering stream, was gathered afresh. Post outlier detection, decline in goodness of fit indices with rise in model complexity was seen. But, there were over all improvements in goodness of fit and in reliability with rise in sample size from 488 to 533, as shown below:

Table 4.149Relationship Between Goodness of Fit, Model Complexity and Sample Size of Different SRL Variables:

SRL Model	Parameter Summary	Variable Summary	DF	CMIN/DF	SRMR	TLI	CFI	RMSEA
COG, METACOG n=488	Weights =14	Total = 15	4	4.420	0.0186	0.974	0.989	0.084
	Variances = 8	Exo = 8						
	Total Parameters= 22	Endo = 7						
COG, METACOG MOT n=488	Weights =32	Total = 33	41	3.227	0.0381	0.95	0.963	0.068
	Variances = 17	Exo = 17						
	Total Parameters= 49	Endo = 16						
COG, METACOG, MOT, BEH n=488	Weights =34	Total = 35	52	2.928	0.0369	0.954	0.964	0.063
	Variances = 18	Exo = 18						
	Total Parameters= 52	Endo = 17						
COG, METACOG, MOT, BEH, EMO **n=488**	Weights = 40	Total = 41	75	6.934	0.1237	**0.813**	**0.846**	0.11
	Variances = 21	Exo = 21						
	Total Parameters= 61	Endo = 20						
COG, METACOG, MOT, BEH, EMO **n=533**	Weights = 40	Total = 41	75	7.532	0.1227	**0.834**	**0.863**	0.11
	Variances = 21	Exo = 21						
	Total Parameters= 61	Endo = 20						

Table 4.150 Comparison of Reliability of the SRL Variables for n=488 and n=533:

S.No.	SRL Variable	Items	Cronbach's Alpha n=533 (n=488)	GLB	Polychoric Ordinal Alpha – C.I. / Point	Polychoric Ordinal Omega	Attenuation Index
1.	Critical Thinking	M47, M51, M66, M71	0.78 (0.78)	0.81	(0.79,0.84) / 0.82	(0.79,0.84)	5 %
2.	Organization	M32, M42, M49, M63	0.77 (0.78)	0.78	(0.79,0.84) / 0.82	(0.79,0.84)	5 %
3.	Planning	P2, P3, P5	0.78 (0.76)	0.76	(0.79,0.84) / 0.81	(0.79,0.84)	6.1 %
4.	Self Recording	P10, P11, P12, P14	0.74 (0.72)	0.77	(0.76,0.82) / 0.79	(0.75,0.81)	6.32 %
5.	Self Evaluation	P15, P16, P18, P20	0.77 (0.77)	0.78	(0.78,0.84) / 0.81	(0.78,0.84)	5 %
6.	Goal Orientation	M1, M16, M22, M24	0.75 (0.73)	0.78	(0.76,0.82) / 0.79	(0.77,0.82)	5.06%
7.	Self Efficacy	M12, M20, M21, M31	0.85 (0.84)	0.87	(0.85,0.89) / 0.87	(0.85,0.89)	2.29 %
8.	Academic Intrinsic Motivation	AIM8, AIM9, AIM10, AIM15. AIM16, AIM17, AIM22, AIM24	0.84 (0.83)	0.89	(0.85,0.88) / 0.86	(0.85,0.88)	2.32%
9.	Future Time Perspective	ZTP12, ZTP13, ZTP14	0.54 (0.48)	0.58	(0.52,0.65) / 0.58	(0.54,0.66)	**6.89 %**
10.	Academic Delay of Gratification	ADG4, ADG8, ADG10	0.56 (0.48)	0.57	(0.61,0.71) / 0.66	(0.61,0.71)	**15.15 %**

11.	Academic Procrastination	AP1, AP2, AP3, AP4	0.65	0.69	(0.67,0.75) / 0.71	(0.68,0.76)	8.45 %
12.	Time and Study Environment	M35, M43, M65, M70	0.73 (0.72)	0.76	(0.74,0.8) / 0.77	(0.75,0.81)	5.19%
13.	Reappraisal	Reapp1, Reapp2, Reapp3, Reapp4, Reapp5	0.63	0.66	(0.63,0.72) / 0.67	(0.64,0.72)	5.97 %
14.	Suppression	Supp1, Supp2, Supp3, Supp4, Supp5	0.54 (0.51)	0.63	(0.54,0.65) / 0.59	(0.55,0.65)	**8. 47 %**

Interpretation: All the estimates of four types of interval and ordinal, point and confidence interval reliability were generated using the R package "userfriendlyscience" (Peters, 2018), and ***there is improvement in the reliabilities for the sample size 533 over the previous sample size of 488***. The ordinal confidence interval reliability coefficients for all the fourteen self regulated learning variables include **the acceptable limit of 0.6 for psychological variables (Kline, 1999; Kyriazos et al., 2018).**

The under estimation of the vital estimate (Chakraborty, 2017) by the notorious interval scale Cronbach's alpha (1951) is also presented for compare and contrast. The attenuation index of the variables academic delay of gratification, future time perspective and suppression are noticeable. **According to Hinton et al. (2004), reliability of a scale is moderate when it is between 0.5 and 0.7**, high when it is between 0.7 and 0.9, excellent when above 0.9 and poor only when it is less than 0.5. As per this standard, even the scales of academic delay of gratification, future time perspective and suppression have moderate reliability. The actual ordinal scale based estimate of the reliability of the fourteen variables lies in the mentioned confidence interval, which includes the threshold value of 0.6, implying acceptable reliability for the SRL variables.

4.12.2 Post-hoc Power Analysis in R using semPower:

Statistical power is one minus the Type II error rate and represents the probability of correctly rejecting a false null hypothesis; this is the probability that an effect will be found in the sample if an effect truly exists in the population. It is important to determine whether a proposed study will have sufficient power to detect an effect if an effect really exists.

> "The purpose of post-hoc power analysis is to determine the actually achieved power to detect a specified effect with given sample size on a certain alpha error. In the language of structural equation modeling, a post-hoc power analysis asks: ***With my sample at hand, how large is the probability (power) to falsify my model if it is actually wrong?***" – Quoting semPower Manual, (Moshagen and Erdfelder, 2016).

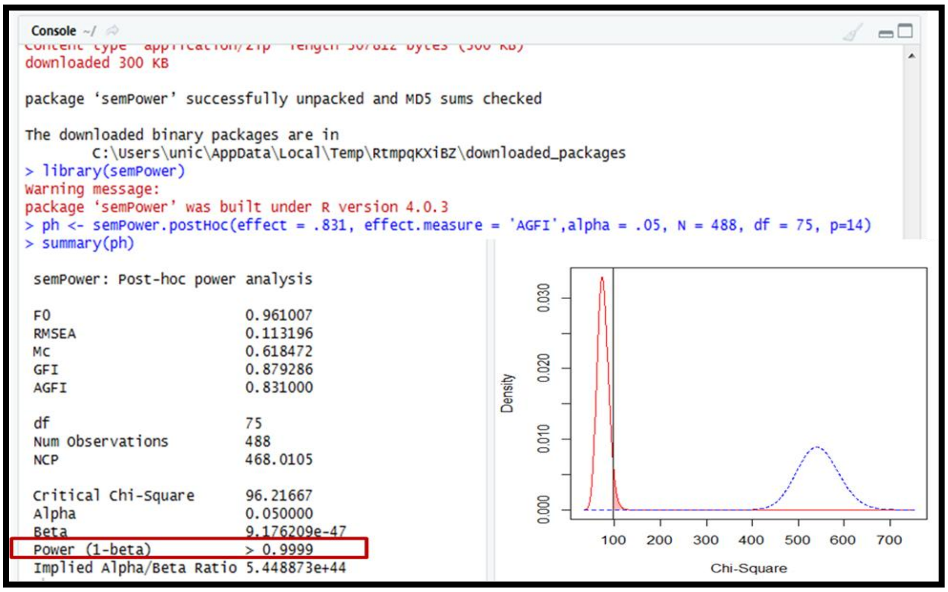


Figure 4.287 **R Codes and Output of Post-hoc Power Analysis n=488**

The power is greater than 0.8 at 0.9999, which proves that there is *enough evidence for the effect to actually exist in the sample*, if SRL with five components exists in the population. AGFI is used as the effect measure here. This is because, in this study, the scales used to measure the 14 variables are of varying Likert scale, an aspect taken into consideration by AGFI while measuring goodness of fit. By obtaining a high power in this study, usage of scales with varying Likert points is also validated. *Hence, objective 4 is achieved.*

When the sample size increased from 488 to 533, there was no change in the estimated power, with its magnitude remaining at 0.999 for new AGFI 0.834 as shown below:

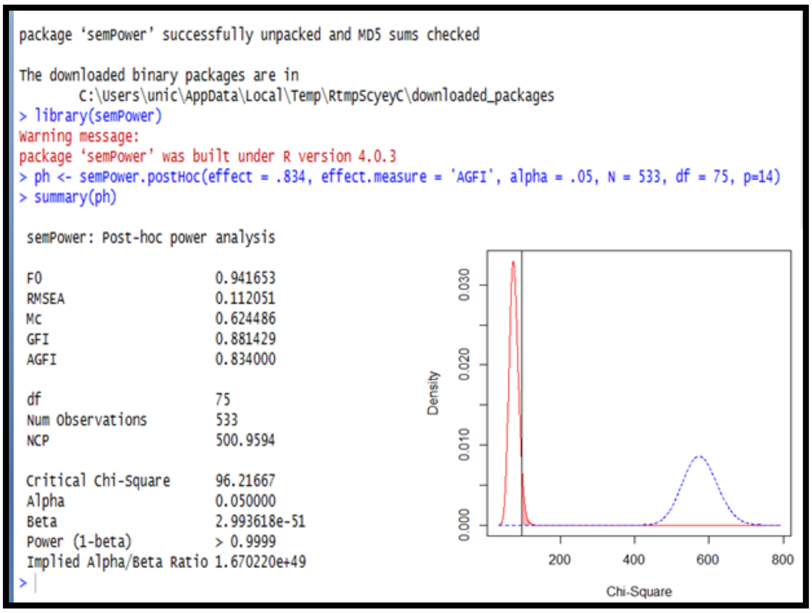


Figure 4.288 **R Codes and Output of Post-hoc Power Analysis n=533**

Conclusion: The power is greater than 0.8 at 0.9999, for n=488 and n=533, which proves that there is enough evidence for the effect to actually exist in the sample in the presence of the existing estimates, when SRL with its five components exists in the population.

4.13 Measurement Invariance Testing of the Revised Integrative Trait Model of Self Regulated Learning among Engineering Undergraduates - Objective 5:

According to Suresh and Chandrashekara (2012), larger sample size gives more power. If the power is high, then, when a significant result is obtained, the researcher can be confident that indeed this is the case. Also, if no difference exists between groups, there can be reasonable confidence that none actually exists. With rise in power, effects undetectable earlier, get detected. To investigate this concept, along with estimation of measurement invariance, a comparison of results for n=488 and for the final sample size of n=533 was done. It is worth mentioning here that the power obtained for both n=488 and for n=533 data analysis was same, that is, above 0.9999.

4.13.1 Measurement Invariance of SRL Model with respect to Gender:

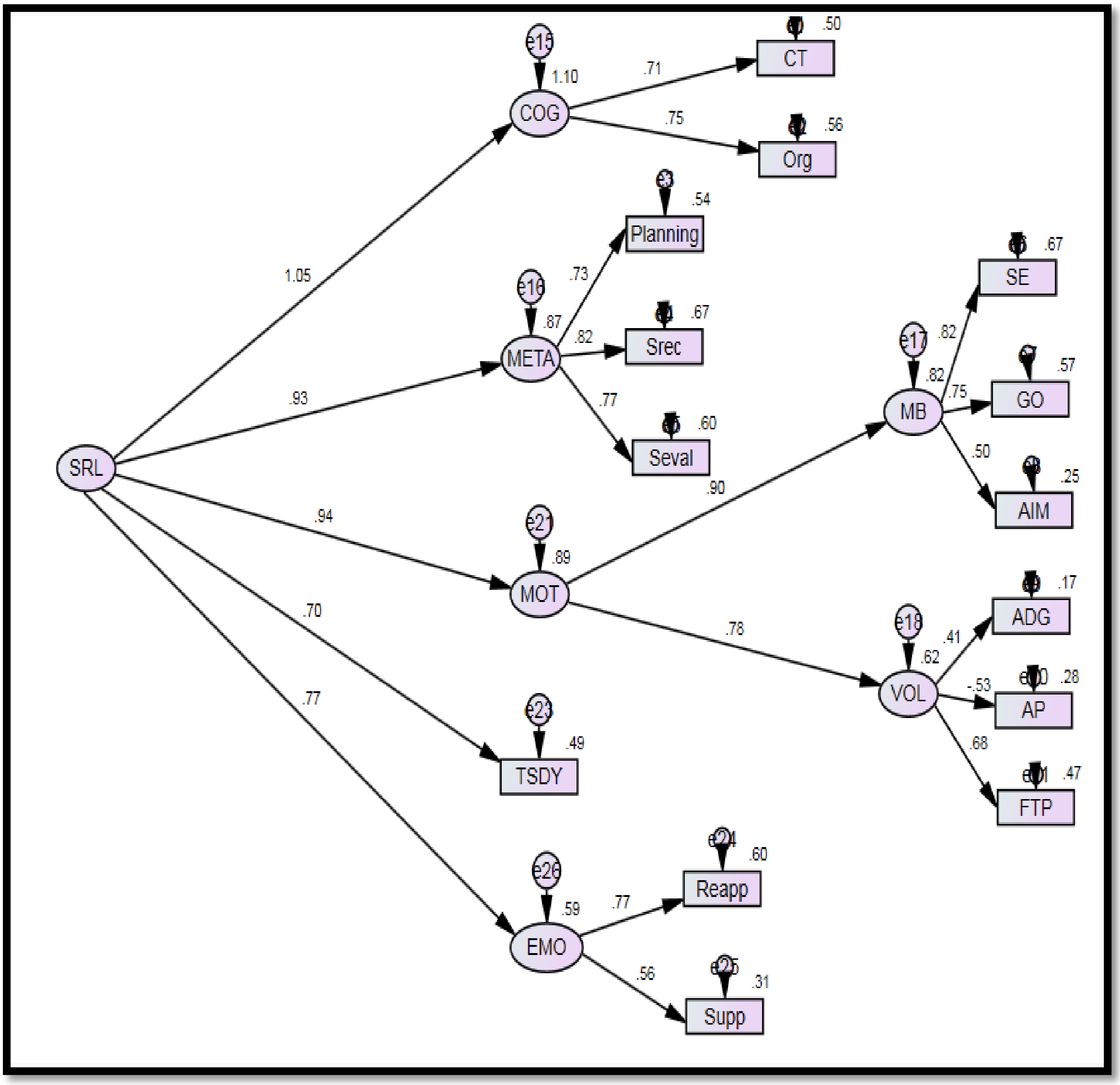


Figure 4.289 **Measurement Invariance of the Revised Integrated Trait Model of Self Regulated Learning with respect to Gender:**

Table 4.151 Goodness of Fit Estimates – Measurement Invariance w.r.t. Gender:

Estimates	"SRMR"	"TLI"	"CFI"	"RMSEA"	Remark	Result
Unconstrained SRL Model	0.1237	0.813	0.846	0.11	**ΔCFI<= 0.01 Cheung and Rensvold Criteria (2002)**	***Invariant***
Constrained SRL Model - Gender	0.1263	0.808	0.842	0.08		
Δ CFI	-	-	0.004	-	**Yes**	

Interpretation: The goodness of fit estimates are acceptable. The Δ CFI difference between the unconstrained and the constrained model are less than the cut-off of 0.01 as set by Cheung and Resnvold (2002), which means that the revised integrative trait model of Self regulated learning is configural measurement invariant with respect to gender, which further imply that the factor structure of construct SRL is same, and the present variables and the items which measure SRL in boys also measure it in girls engineering students.

When the sample size was increased from 488 to 533, the unconstrained model saw rise in estimates of CFI (from 0.846 to 0.863) and TLI (from 0.813 to 0.834), but not much change in SRMR (from 0.1237 to 0.1227) and RMSEA (no change from 0.11). This result is as per the nature of the estimands with sample size change.

When the constrained model goodness of fit with respect to gender was obtained for increased sample size of 533, the SRMR was 0.1217, RMSEA was 0.081, CFI was 0.859 andTLI was 0.829. The Δ CFI difference was 0.004, less than 0.01, proving the previous result for n=488, that the revised model of trait based self regulated learning is gender invariant.

4.13.2 Measurement Invariance of SRL Model with respect to Stream:

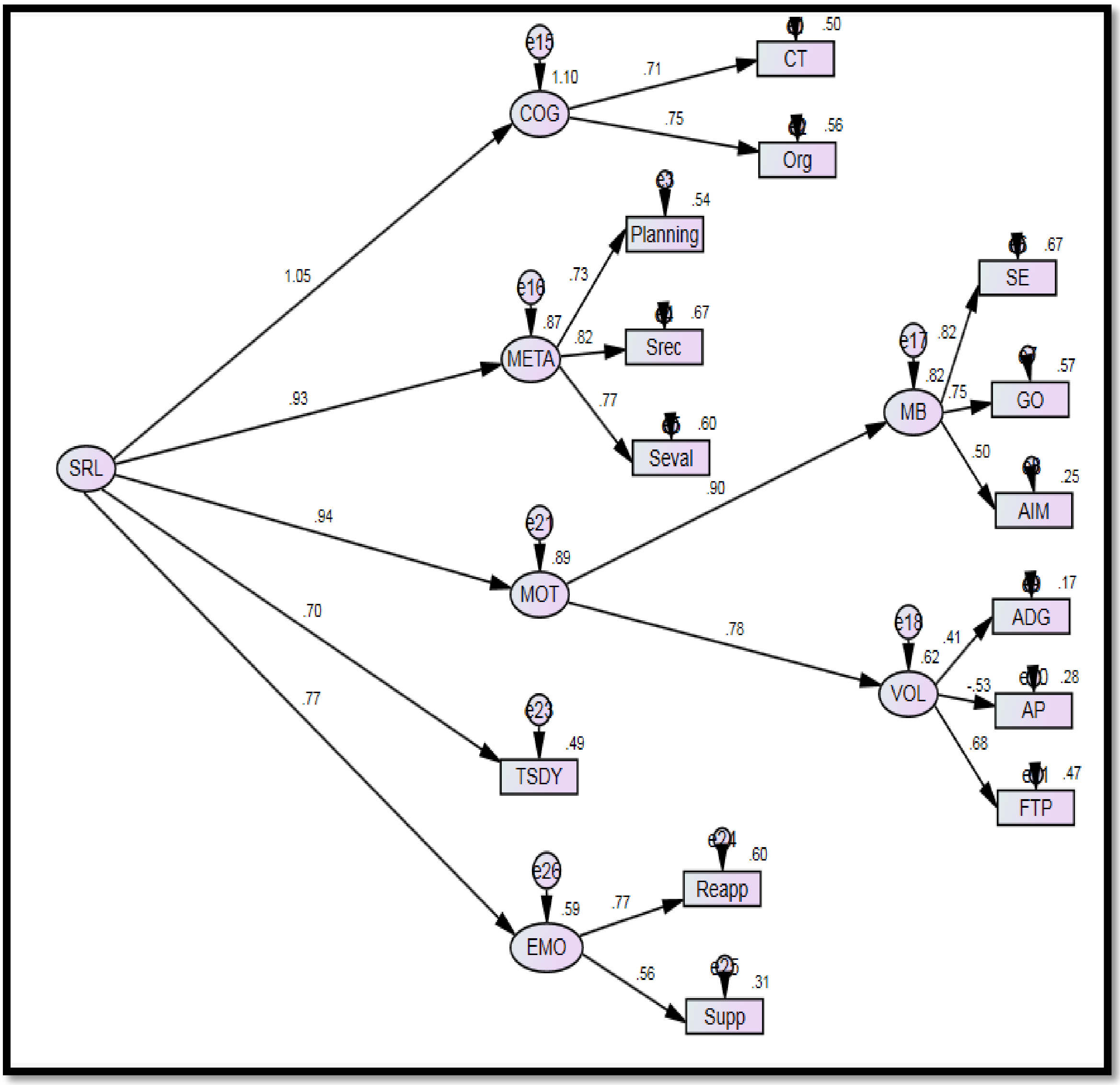


Figure 4.290 **Measurement Invariance of the Revised Integrated Trait Model of Self Regulated Learning with respect to Stream**

Table 4.152 Goodness of Fit Estimates – Measurement Invariance w.r.t. Stream:

Estimates	SRMR	TLI	CFI	RMSEA	Remark	Result
Unconstrained SRL Model	0.1237	0.813	0.846	0.11	**ΔCFI<= 0.01 Cheung and Rensvold Criteria (2002)**	***Invariant***
Constrained SRL Model - Stream	0.1157	0.81	0.842	0.078		
Δ CFI	-	-	0.004	-	**Yes**	

Interpretation: The goodness of fit estimates are acceptable. The Δ CFI difference between the unconstrained and the constrained model are less than the cut-off of 0.01 as set by Cheung and Resnvold (2002), which means that the revised integrative trait model of Self regulated learning is configural measurement invariant with respect to stream, which further imply that the factor structure of construct SRL, the present variables and the item which measure SRL in Computer science engineering students also measure it in Mechanical engineering students.

When the sample size was increased from 488 to 533, the unconstrained model saw rise in estimates of CFI (from 0.846 to 0.863) and TLI (from 0.813 to 0.834), but not much change in SRMR (from 0.1237 to 0.1227) and RMSEA (no change from 0.11). This result is as per the nature of the estimands with sample size change.

When the constrained model goodness of fit with respect to stream was obtained for increased sample size of 533, the SRMR was 0.1142, RMSEA was 0.079, CFI was 0.861 and TLI was 0.831. The Δ CFI difference was 0.002, less than 0.01, proving the previous result for n=488, that the revised model of trait based self regulated learning is stream invariant.

4.13.3 **Measurement Invariance of SRL Model with respect to Batch:**

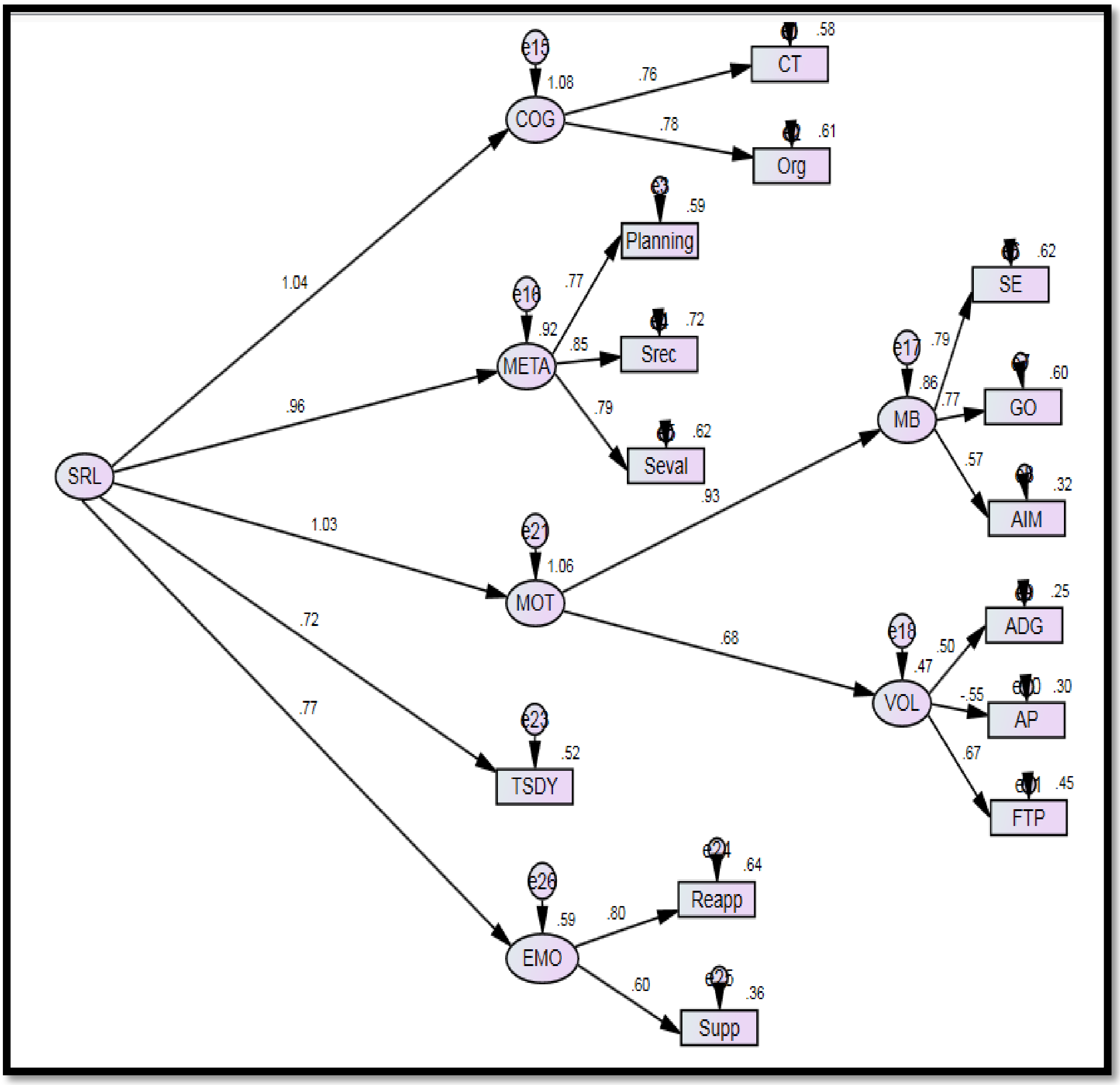


Figure 4.291 **Measurement Invariance of the Revised Integrated Trait Model of Self Regulated Learning with respect to Batch**

Table 4.153 Goodness of Fit Estimates – Measurement Invariance w.r.t. Batch:

Estimates	SRMR	TLI	CFI	RMSEA	Remark	Result
Unconstrained SRL Model	0.1237	0.813	0.846	0.11	**ΔCFI<= 0.01 Cheung and Rensvold Criteria (2002)**	***Variant***
Constrained SRL Model –Batch (n=488)	0.1271	0.8	0.834	0.082		
Δ CFI (When n=488)	-	-	0.012	-	**No**	
Unconstrained SRL Model (n=533)	0.1227	0.834	0.863	0.111	**ΔCFI<= 0.01 Cheung and Rensvold Criteria (2002)**	***Invariant***
Constrained SRL Model – Batch (n=533)	0.129	0.821	0.853	0.082		
Δ CFI (When n=533)	-	-	0.010	-	**Yes**	

Interpretation: The goodness of fit estimates are acceptable. The Δ CFI difference between the unconstrained and the constrained model was more than the cut-off of 0.012 as set by Cheung and Resnvold (2002).

However, when the sample size was increased from 488 to 533, the unconstrained model saw rise in estimates of CFI (from 0.846 to 0.863) and TLI (from 0.813 to 0.834), but not much change in SRMR (from 0.1237 to 0.1227) and RMSEA (no change from 0.11) was seen. This result is as per the nature of the estimands with sample size change.

When the constrained model goodness of fit with respect to batch was obtained for increased sample size of 533, the SRMR was 0.129, RMSEA was 0.082, CFI was 0.853 and TLI was 0.821. The Δ CFI difference was 0.010, which is in accordance to the Cheung and Rensvold (2002) criteria of measurement invariance, proving that ***with the rise of the sample size, power of the study also increased***, detecting a vital change in the result, which is that the revised model of trait based self regulated learning is also batch invariant. It means that the revised integrative trait model of self regulated learning is configural measurement invariant with respect to batch, which further imply that the factor structure of the construct SRL, i.e, the variables, and hence the items measuring it, are the same for IInd year and IIIrd year engineering students. ***The null hypothesis H_0 of the revised integrative trait model of self regulated learning being measurement invariant, across groups, with respect to gender, batch and stream, in the Indian context, is accepted***. *Hence, objective five is achieved.*

4.14 Latent Profile Analysis (LPA) of the Sample Subjects Based on their Self Regulated Learning:

The extraction of profiles as part of latent profile analysis is conducted using the *tidyLPA* package of R Ver. 3.6.3. along with the package *dplyr*. Model 1 where the variance is equal and covariance is zero was selected to estimate the profiles. Help of estimands AIC, BIC, entropy and BLRT- p value were taken to finally settle for the number of profiles. The function compare_solutions() helps in comparing the goodness of fit of multiple models with different profiles and model specifications. The graphical representation of the profiles was presented by plot-profile function.

R Codes and Results of Latent Profile Analysis:

1. Import data file in r
2. Install.packages("tidyLPA")
3. Library(tidyLPA)
4. Install package dplyr
5. Library (dplyr)

```
> LPA_533%>%select(SRL)%>%single_imputation() %>% estimate_profiles(3)
tidyLPA analysis using mclust:

Model Classes AIC     BIC     Entropy prob_min prob_max n_min n_max BLRT_p
1     3       1124.92 1150.59 0.36    0.45     0.75     0.19  0.59  0.87
> LPA_533%>%select(SRL)%>%single_imputation() %>% estimate_profiles(4)
tidyLPA analysis using mclust:

Model Classes AIC     BIC     Entropy prob_min prob_max n_min n_max BLRT_p
1     4       1128.84 1163.07 0.34    0.18     0.70     0.05  0.48  0.67
```

```
>LPA_533%>%select(SRL)%>%single_imputation() %>% estimate_profiles(5)
tidyLPA analysis using mclust:

Model Classes AIC     BIC     Entropy prob_min prob_max n_min n_max BLRT_p
1       5      1131.68 1174.46   0.39     0.10        0.77       0.03     0.49     0.37

> LPA_533%>%select(SRL)%>%single_imputation() %>% estimate_profiles(6)
tidyLPA analysis using mclust:

 Model Classes AIC     BIC     Entropy prob_min prob_max n_min n_max BLRT_p
 1       6      1129.91 1181.25  0.62     0.22        0.85       0.01    0.35      0.14
> LPA_533%>%select(SRL)%>%single_imputation() %>% estimate_profiles(2)
tidyLPA analysis using mclust:

 Model Classes AIC     BIC     Entropy prob_min prob_max n_min n_max BLRT_p
 1        2      1120.58 1137.69  0.57     0.69       0.94       0.22     0.78     0.01
> LPA_533%>%select(SRL)%>%single_imputation() %>% estimate_profiles(1)
tidyLPA analysis using mclust:

 Model Classes AIC     BIC     Entropy prob_min prob_max n_min n_max BLRT_p
 1       1      1131.95 1140.51   1.00     1.00        1.00        1.00      1.00

> LPA_533 %>% select(SRL)%>%single_imputation() %>% estimate_profiles(1:3,
variances = c("equal", "varying"), covariances = c("zero",
"varying"))%>%compare_solutions(statistics = c("AIC", "BIC"))
Compare tidyLPA solutions:

 Model   Classes   AIC      BIC
   1         1       1131.948 1140.505
   1         2       1120.580 1137.694
   1         3       1124.919 1150.590
   2         1       1131.948 1140.505
   2         2       1122.796 1144.189
   2         3       1128.766 1162.994

Best model according to AIC is Model 1 with 2 classes.

Best model according to BIC is Model 1 with 2 classes.
```

An analytic hierarchy process, based on the fit indices AIC, AWE, BIC, CLC, and KIC (Akogul and Erisoglu, 2017), suggests the best solution is Model 1 with 2 classes. Here, model 1 is the least strict model and model 2 is the highest in strictness.

Table 154: Summary of Model 1 Specifications: Latent Profile Analysis of Self Regulated Learning

Model	Classes	AIC	BIC	Entropy	Prob_min	Prob_max	n_min	n_max	BLRT_p
1	1	1131.95	1140.51	1.00	1.00	1.00	1.00	1.00	-
	2	**1120.58**	**1137.69**	**0.57**	**0.69**	**0.94**	**0.22**	**0.78**	**0.01**
	3	1124.92	1150.59	0.36	0.45	0.75	0.19	0.59	0.87
	4	1128.84	1163.07	0.34	0.18	0.70	0.05	0.48	0.67
	5	1131.68	1174.46	0.39	0.10	0.77	0.03	0.49	0.37
	6	1129.91	1181.25	0.62	0.22	0.85	0.01	0.35	0.14

Interpretation: The BIC and AIC are the lowest, 1137.69 and 1120.58 respectively, for the class with profiles 2, in the most popular model 1. The goodness of fit between the model and the data is very significant with p-value less than 0.05 at 0.01of the estimand BLRT_p-value only for this class 2, with its profiles termed as the high SRL, and the low SRL. For rest of the classes, the p-value is non-significant and hence they are not considered for further analysis.

The entropy of class 2 is 0.57, which means that 57 percent of the cases of total 533, that is 304 cases, were properly classified into their most probable profile. 69 percent of the cases belonging to the lowest profile could be properly classified under this category as the Prob_min is 0.69. Since Prob_max is 0.94, it means that 94 percent cases belonging from the higher profile were properly classified into its respective category. The number of cases in the lowest profile is 117 as the n-min is 0.22. The number of cases in the highest profile is thus 416, since the n-max is 0.78.

```
> LPA_533%>%select(SRL)%>%single_imputation() %>%
estimate_profiles(2)%>%plot_profiles()
```

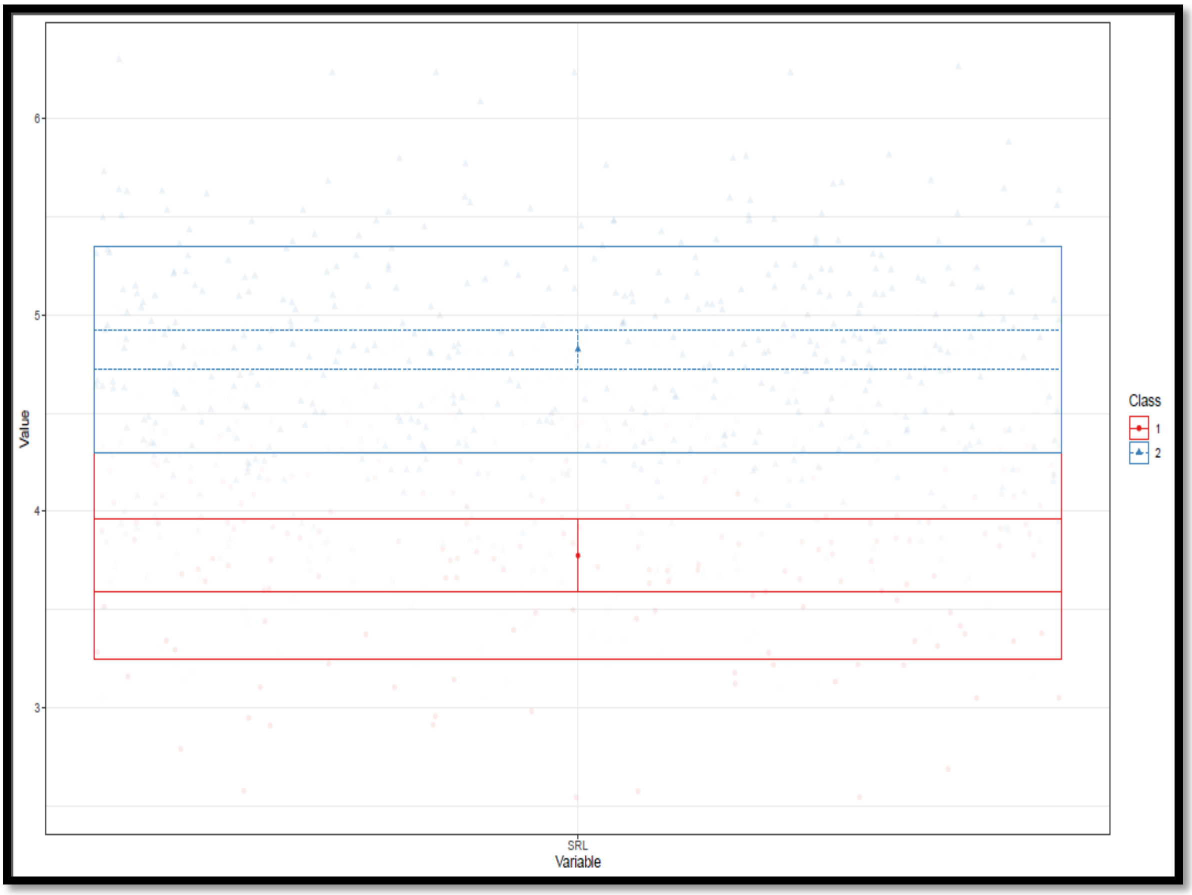


Figure 4.292 **Two Latent Profiles of Self Regulated Learning**

Interpretation: The lower SRL profile with 117 subjects (22 percent), represented as class 1 in the above plot, is consistently low across the variable SRL. The higher SRL profile with 416 subjects (78 percent), represented as class 2, is consistently high across the SRL variable, and is distinct from the lower SRL profile, implying that the 533 engineering undergraduates, forming the sample subjects of this study, can be grouped into two profiles based on their self regulated learning trait.

Conclusion: The revised integrative trait model of self regulated learning among engineering undergraduates of Punjab state is found to be measurement invariant with respect to gender, batch and stream. Two profiles of self regulated learning, namely the higher and the lower, were extracted from the sample subjects of this study.

In the next chapter, the overview of the study, its findings, educational implications, limitations and recommendations for future studies would be discussed.

CHAPTER 5

OVERVIEW, FINDINGS, EDUCATIONAL IMPLICATIONS, LIMITATIONS, RECOMMENDATIONS AND SUGGESTIONS FOR FUTURE RESEARCH

5.1 Introduction:

This chapter presents an overview of the research work, its findings, educational implications of the findings, limitations, recommendations and suggestions for future research. The overview would provide the backdrop against which the research work was conceived and the vital objectives framed to seek their solution. The findings section would bring the results of the study to a perspective. This exercise would be followed by a discussion on the implications of the study on the Indian engineering education landscape. The areas uncharted in this work would be mentioned in the limitations. Finally, the road ahead in research would be chalked out in the recommendations and suggestions for further study sections.

5.2 Overview of the Study:

According to the India Skill Report (2020), prepared by Wheebox, a leading online talent assessment company, in partnership with the Confederation of Indian Industry (CII) and All India Council for Technical Education (AICTE), the most employable talent in the country rests in the domain of engineering and technology graduates. These graduates topped the chart for the past seven years since 2014. The most number of candidates hired are engineers in comparison to other domain candidates. These findings make explicit the apparent significance of the engineering domain, as the primer of the labour work force and successively the economy of India. During recruitment of the engineering undergraduates, the student’s academic achievement serves as an apparent quantitative indicator of the presence of the preferred skills by the employer. Another factor highly valued by the employers in the students is their learning agility which requires an intent of life long learning in them even after they are hired. The link between the academic achievement of a to-be hired engineering student and a life long learning employee, with learning agility, is the aspect of self regulated learning. Owing to their autonomous nature, self regulated learners not only perform well in academics but also continue to upgrade their knowledge, skill and attitude all along their life.

As a psychological construct, the literature of self regulated learning originated with the pioneering work of Bandura through his social-cognitive theory around 1986 and later extended by Zimmerman, Pintrich and other educational psychologists. With advancement in the understanding about the components that make up this construct, an attempt to develop an empirical model to measure it in students was also initiated. The latest trait based model was put forth by Dorrenbecker and Perels (2015), which included the cognitive, metacognitive and motivational components of self regulated learning. The priced contribution of this work was the establishment of volition as a sub-component of motivation alongwith motivational belief. But, literature mentioned self regulated learning to be made up of two more components, namely, the behavioral and the emotional components. The present study aimed to search and validate an instrument to measure the emotional component of SRL, cross-validate the work of Dorrenbecker and Perels on volition in the Indian context, club the two with the behavioral component and extend the previous work, to present a comprehensive, revised integrative trait model of self regulated learning among engineering undergraduates of Punjab state.

5.3 Findings of the Study:

The findings of the study are discussed objective-wise as follows:

Objective 1: To validate the trait model of emotional self regulated learning in the Indian context.

a. The factor structure of trait based academic emotional regulation strategies was found to be valid in the Indian context as was found to be so by Buric et al. (2016) in the Croatian context, using both conventional techniques of exploratory factor analysis (EFA) and maximum likelihood estimator (ML) based confirmatory factory analysis (CFA), and a new state of the art approach of Network Psychometrics, involving Exploratory Graph Analysis (EGA) and robust WLSMV estimator based confirmatory factor analysis.

b. The reliability of the eight dimensions of AERQ was found to be acceptable using the traditional Cronbach's alpha and the lesser known polychoric ordinal reliability. The underestimation of the true reliability of Cronbach's alpha was shown by calculating the attenuation index. The concept of structural consistency which married the concepts of internal consistency with external consistency or homogeneity of items under network psychometrics based reliability and the obtaining of good estimates of this estimand for all the eight dimensions of the construct, provided added validation for the objective one of this study.

c. This work further validates the Process model of emotional regulation theory by Gross (1998) and subsequent qualitative research by Buric et al. (2016), based on which the factor structure of academic emotional regulation strategies is conceived.

Objective 2: To validate the trait model of volitional self regulated learning in the Indian context.

a. The volitional component of self regulated learning, originally validated by Dorrenbecher and Perels (2015) in the German context, was found to be valid in the Indian context as well, both by using the conventional approach of EFA and CFA, and by Network Psychometrics based EGA and robust CFA. .

b. Both the approaches established through excellent estimates that volition can be measured using the candidate variables, academic delay of gratification, future time perspective and academic procrastination, achieving objective two.

c. In order to introduce good practices of reliability analysis when dealing with ordinal responses of Likert-scale questionnaires, the present study presented the estimation of polychoric omega which is based on tetrachoriccorrelation using R. Using the package psych, the codes to generate this vital estimate of reliability, instead of the erroneous Cronbach' alpha, was shared in the article reporting this finding.

Objective 3: To validate the role of trait volition in the revised integrative trait model of self regulated learning in the Indian context.

a. In the present study, two models of revised integrative self regulated learning were compared for validation.

b. The first model included volition as a sub component of motivation component along side motivational belief, and further extended Dorrenbacher's model by including the emotional and behavioral components of self regulation.

c. The second model involved six components of self regulation, namely, cognitive, metacognitive, motivational, volitional, behavioral and emotional separately. Both the models had SRL as the latent variable predicting academic achievement of second year and third year computer science and mechanical engineering students, for providing construct validity to the factor structure.

d. The results, through BIC and AIC estimands, clearly showed that the model 1 had lower estimates of BIC and AIC and proved to be a better model than model 2, and significantly predicted academic achievement.

Objective 4: To validate the revised integrative trait model of self regulated learning in the Indian context

a. The revised integrative trait model of self regulated learning in the Indian context was found to be possessing moderate goodness of fit estimates. The goodness of fit, in general, declines with the rise in the complexity of the model, as found in literature. McNeish, An and Hencock (2017) warned that the Hu and Bentler simulation based cut-off indices recommendations are highly susceptible to quality of measurement of models and Jackson et al. (2009) found that the scientific community at large does not heed well the warnings of Hu and Bentler against strict adherence to their cut-offs. Moreover, Hancock and Mueller (2011) coined the term “Reliability paradox” to drive home the point that poorer quality measurement often display better data-model fit estimates and better quality measurement tend to display worse data-model fit.

b. Though the goodness of fit estimates were moderate, due to complexity of the model, the help of post hoc power analysis was sought using semPower package in R. The estimand adjusted goodness of fit index AGFI was the estimator to calculate the power. The adjusted goodness of fit was chosen in the study, due to the use of scales of different self regulated learning variables with varying Likert scale responses. Compared to goodness of fit index GFI, AGFI takes this aspect of data collection into consideration. The power obtained was very high, proving that the phenomenon existing in the population, of self regulated learning consisting of five components as proposed in the model, was captured with sufficient evidence by the sample data.

Objective 5: To validate the measurement invariance of the revised integrative trait model of self regulated learning across groups, with respect to gender, batch and stream, in the Indian context.

a. The final objective of the study was to investigate whether the factor structure of the model is intact or whether the construct self regulated learning was conceptualized the same by male and female engineering students, from computer science and mechanical stream, and belonging to the crucial second and third years, or not, through Configural measurement invariance testing (Riordan and Vandenberg, 1994).

b. The SEM based framework, using Confirmatory Factor Analysis (CFA) was applied to test the measurement invariance of the revised integrative trait model of self regulated learning among engineering undergraduates, with respect to gender, stream and batch.

c. The proposed factor structure of revised integrative trait model of self regulated learning was found to be measurement invariant (MI) with respect to gender, steam and batch of the engineering undergraduates.

d. The latent profile analysis (LPA) of the self regulated learning scores of the engineering undergraduates, extracted two distinct profiles, namely, high and low.

5.4 Educational Implications of the Study:

a. The World Bank recommends four critical areas to focus in order to promote knowledge-based economies for countries across the world, based on the tested models of Finland, Ireland and Korea (Abu-Goukh, Ibraheem and Goukh, 2012). These critical areas are:

i. A population that is literate and skilled

ii. A dynamic information infrastructure

iii. An institutional regime that lets free flow of knowledge and makes ample investment in information and communication technology along with promotion of entrepreneurship.

iv. A wide networks of think tanks, research institutions, universities that can make use of the growing body of knowledge and adopt it to meet the local requirements and develop new knowledge.

b. It is critical that the population of a country possesses the right knowledge, skill and competencies that are required to use knowledge for development and to become knowledge based economy. A significant reason for the success of the mentioned type of economy in Finland, Ireland and South Korea is due to the substantial amount of changes and investments these countries made in their science and technology education, realizing the intimate relationship engineering and technology share with economic growth of the nation. This concept is ingrained in the very definition of the profession of engineering which is “the profession in which a knowledge of the mathematical and natural sciences gained by study, experience, and practice is applied with judgment to develop ways to utilize economically, the materials and forces of nature for benefit of mankind”, Goukh (2011).

c. In India, owing to its close relationship with the manufacturing and infrastructure sectors, the engineering sector is of strategic importance to the country's economy. Making significant strides towards becoming a knowledge based economy by developing its engineering sector, India became a permanent signatory of Washington Accord (WA) in June 2014. As a result, it is now a permanent member in the elite group of 17 nations which have an agreement on engineering studies and mobility of engineers from one signatory nation to another.

d. The last and the 12th element of an engineering graduate's attributes (defined as "the qualities, skills and understandings a university community agrees its students would desirably develop during their time at the institution and, consequently, shape the contribution they are able to make to their profession and as a citizen", Bowden et al., (2000); Nair, Patil and Mertova, (2009)) according to this accord, WA-12, is that he or she should be a self regulated and life long learner, as quoted below from the report:

"WA12: Recognise the need for, and have the preparation and ability to engage in, independent and life-long learning in the broadest context of technological change".

-Pp:15, The Washington Accord Graduate Attribute Profile,

-25 Years Washington Accord (1989-2014).

e. Development of self regulated strategies at university level for preparing the students to meet the demands of autonomous learning later in life, is thus the need of the hour (Capote, Rizo and Bravo, 2017). However, research on the topic of self regulated learning in the domain of engineering education is in its early stage globally **(**Nelson et al., 2015; Saez et al., 2020**)**, leave alone India's status of research in engineering education, where there is scarcity of work (Sahu et al., 2013).

f. The gender, stream and batch invariances of the model presented through this research, further add to the benefits of its administration on all students belonging two of the most sought after streams of engineering education.

g. The availability of this measurement invariant model and its measurement invariant tool would also address the issue of sophomore slump, by profiling students at the earliest, once the retention rate stabilizes after the transient period of first year of engineering.

h. With the presence of data on the extent of self regulation present in the students of an institution, the appropriate interventions in the curriculum can be initiated to come up with customized courses for the students of different profiles of SRL. Instruction of profile specific engineering courses would then lead to rise in the motivation levels of the sophomores as they would be able to relate more with their studies.

i. This would further enhance their academic achievement, ultimately bringing down the dreaded drop-out due to poor performance in engineering educational institutions. Subsequently, more number of quality engineering graduates would pass out from the educational institutions, putting a probable end to the prevalent compromises made with the standards of this professional education. It is worth mentioning here that according to the 2018 Science and Engineering Indicators report by the National Science Board, the United States, India tops in the number of science and engineering degress awarded by universities to graduates, in the world with 25%, followed by China with 22%. Both these nations together produce nearly half of the sciences and engineering graduates across the world. In this context, apart from the quantity, the quality of these graduates hinges on the research conducted in self regulated learning in science and engineering.

j. The presence of a comprehensive and measurement invariant model with its tool can hopefully promote self regulated learning research in the country along with certain state of the art good practices observed in this study, like conducting parametric and non parametric item response theory based differential item functioning and ant-colony optimization algorithm to select items for a psychological instrument, cross validation of the exploration and confirmation of factors using network psychometrics parallel to the conventional exploratory and confirmatory analysis, measurement invariance of the model / tool across gender and other vital demographic groups, and reporting of ordinal polychoric and structural consistency based reliability.

k. The extraction of two profiles, high SRL and low SRL, through latent profile analysis of the final data, reveals that there is individual difference in the subjects with respect to self regulated learning, further driving the point home of developing customized intervention programs for the promotion of this vital construct in engineering institutions.

l. The sharing of R codes to conduct the mentioned statistical techniques and their easy availability in the Internet would also promote conducting of research using open source software.

5.5 Limitations of the Study:

a. Comparatively little research has taken place on self regulated learning in engineering education across the world. The severity of the challenges posed by the issues associated with engineering education and its apparent significance due to its close proximity to economy of the country requires instant attention in the Indian context. It implies that there is a scarcity of quality research on self regulated learning within engineering education domain in our country.

b. There was a mixed sense of cooperation from the engineering institutions contacted through physical visit or through online mode for acquiring the permission to gather data. While certain institutions ensured that the entire exercise of data collection was conducted through proper channel, other institutions, kept the exercise informal. A couple of institutions denied the permission to collect data from their students in either of the modes. Due to time and budget constraint, the data gathered was cross-sectional in nature and measured a time snapshot presence of the components of self regulated learning in the subjects.

c. Due to the spread of the epidemic COVID-19 in the year 2020, a major part of data collection took place through the online mode using a google form. The extent of data collection reduced when its mode changed from physical to online, though the ease of voluntary participation of the subjects and access of the filled data to the investigator remained unchanged.

d. There are dissimilar number of participants from the second and third year batches of computer science and mechanical engineering streams, owing to the online mode of data collection. Contrary to the physical mode of data collection, in spite of the ease in filling the responses and gathering the data, a researcher cannot create an inclusive environment for the subjects to provide their response coherently at once. After repeated reminders and assurances of confidentiality of their responses, the participants fill the online questionnaire at their own discretion or shy away from the exercise.

e. There were very little number of female participants from the stream of mechanical engineering and the female participants were predominantly belonging to the stream of computer science and engineering. A consequence of this was that DIF of Items of Scale 3, 4 and 5 – Planning, Self recording and Self Evaluation could not be generated since the sample subjects of the pilot study were all male subjects pursing Mechanical engineering.

f. Also, unequal number of sample size of the compared groups (Male =373; Female = 160 w.r.t. Gender), (Computer Science = 344; Mechanical = 189 w.r.t. to Stream) and (IInd year = 292; IIIrd year =241 w.r.t. Batch) always poses a threat of the failure in the detection of noninvariance. It is because in such cases, the group with larger sample size has larger influence on the parameter estimation of the constrained model (Cheung and Lau, 2011).

g. Though the revised model is found to be invariant with respect to batch in the present study for the sample size of n=533, it is worth mentioning that this result is on the borderline as per Cheung and Rensvold (2002) criterion and is a deviation from certain findings on the topic, present in the limited available literature. The developmental course of SRL, that is, how students' SRL skills and strategies change over time, received less attention in the literature (Hoyle and Dent, 2017; Panadero, 2017). Previous studies taking a longitudinal approach to examining SRL or relevant constructs across grade levels, occurred mostly at the elementary and secondary education levels, which are also less in number considering the growing body of literature on SRL in different school contexts (Harding et al., 2019).

i. Harding et al., (2019) found that SRL decreased in students as the grade level increased from 5th to 8th class. Guo (2020) found that SRL decreased with age in a study comprised of 1260 Chinese students of 10th, 11th and 12th grades. These recent findings are consistent with results of previous research studies (Cleary and Chen, 2009; Hong et al., 2009; Lau, 2009; Yueng et al., 2011; Huang, 2013; Wigfield et al, 2015; Gaspald et al., 2017).

Table 5.1 Measurement Invariance Testing usingSteiger's Gamma Hat (1989):

S.No.	**Model**	**Number of Variables**	**df**	**RMSEA**	**Gamma Hat**	**Δ Gamma Hat <=0.001**	**Result**
1.	Unconstrained	14	75	0.111	0.88	-	
2.	Constrained Gender	14	150	0.081	0.88	0	***Invariant***
3.	Constrained Stream	14	150	0.079	0.88	0	***Invariant***
4.	Constrained Batch	14	150	0.082	0.87	0.01	***Variant***

Table 5.2 Measurement Invariance Testing usingMcDonald's NCI (1989):

S.No.	**Model**	**Chi-Square**	**df**	**N**	**NCI**	**Δ NCI < 0.02**	**Result**
1	Unconstrained	564.915	75	533	0.631	-	-
2	Constrained - Gender	666.193	150	533	0.6156	0.0154	***Invariant***
3	Constrained - Stream	641.927	150	533	0.6298	0.00119	***Invariant***
4	Constrained - Batch	683.946	150	533	1.6517	-1.02072	***Variant***

NOTE: In the case of non-centrality index NCI estimation for batch, its value crossed 1 which is legitimate according to McDonald (1989).

j. There are a limited number of longitudinal studies available that examined college student samples on this issue (Kumar et al., 2018; Coertjens et al., 2017; De Clercq et al., 2013; Fryer, Ginns, and Walker, 2016; Severiens, Ten Dam, and Wolters, 2001).Coertjens et al. (2017), as cited by Jeong (2019), found that students' self-regulation remained constant during their first-year in college but it increased from the end of the first year to the beginning of the second year. Kumar et al. (2018) found that self directed learning readiness significantly decreased in medical students from the time of their admission to final internship in India. Their results suggest that students vary in their SRL development with respect to batches or grade levels.One of the reasons cited for SRL varying with grade, is that as students age, they may re-evaluate their capabilities and change their self-perceptions (Yueng et al., 2011). This discussed aspect of the result holds significance in the context of two lesser reported methods of establishing measurement invariance, known as the Steiger's ΔGamma Hat (1989) calculated using Fan and Sivo (2007) formula (Gamma= Number of variables / (Number of variables)+(2*df*(RMSEA squared))) and ΔMcDonald's NCI (1989) formula (M_c = exp(-1/2[(T_T – df_T]/N-1), where M_c is McDonald's non-centrality index NCI, T_T is the chi-square value of the model, df its degree of freedom and N the sample size. In the present study, these alternative fit indices of measurement invariance were also calculated using an excel sheet calculator available online and manually respectively (refer Table 5.1 and 5.2), since according to Cheung and Rensvold (2002), similar to ΔCFI, they are also unaffected by model complexity and sample size, and not related to overall fit measures.

k. The more prevalent Likelihood Ratio Test (LRT) method for testing measurement invariance was not applied in this study owing to its pronounced dependence on chi-square estimand and sensitivity to large sample (Brannick, 1995; Kelloway, 1995).

l. Psychometrically, the literature of multi-group measurement invariance is evolving yet, along with the search for a gold standard to establish MI across groups. Also, the evaluation of a model is done by treating the data to be continuous using the maximum likelihood estimator, whereas the responses collected during the Likert scale are ordinal in nature, which requires the use of WLSMV as the estimator. However, the research on cut off values of model selection when dealing with categorical WLSMV based estimation is still developing.

m. The model fit estimation for complex models is still an area of research requiring much progress. The field of Network psychometrics which provides a state of the art approach of factor exploration and confirmation considering the reality of interconnectedness of the items and factors among themselves, instead of being liner reflections, is also in its nascent stage.

n. The reliability of the variables academic delay of gratification, suppression and future time prespective is relatively low. This estimand can be improved for academic delay of gratification and future time perspective variables by including more items to measure them from their psychometrically well established / validated original scales. However, the sub scale of suppression is comparatively new (Buric et al., 2016) and its low reliability in the present study warrants the need to conduct further validation exercises of the Academic Emotion Regulation Questionnaire (AERQ) in multiple contexts in India and abroad for gaining clearer insight on the reliability of this sub scale.

o. In the present study, the analysis of measurement invariance is stopped at Configural invariance and not extended to metric and higher levels of measurement invariance testing with respect to gender, batch and steam. It is because further replication studies must be first conducted to firmly establish the basic configural invariance of the revised integrative trait model of self regulated learning in multiple groups and contexts. It will subsequently confirm that the variables chosen to represent the five respective components of self regulated learning are proper and capable to capture the individual difference in this complex construct. Also, such research will lead to the existence of certain literature which shows the effect size of configural invariance of the revised integrative trait model of self regulated learning. Later, tests to establish the invariance of the items chosen across multigroups through the metric invariance can be taken up. Hierarchical measurement invariance tests are primarily dependent on unconstrained model's fit indices and thus the establishment of the factor structure of self regulated learning across multiple groups and contexts through future studies is initially necessary.

5.6 Recommendations:

The results obtained in the present study form the basis for following recommendations:

a. Engineering institutions are recommended to initiate administration of the measurement invariant model's tool of this study on their students to measure and profile them based on the extent of self regulation present in them. This information can be further processed in the development of profile based intervention programs to promote this vital construct in the learners from the second year of the engineering program for adequately addressing the issue of sophomore slump and retention of students from dropping out.

b. It is recommended in general that the exploration and confirmation, finally leading to the validation of any psychological instrument can hence forth be augmented using Network Psychometrics based exploratory graph analsis (EGA) and robust confirmatory factor analysis, and Ant Colony Optimization (ACO) algorithm, using the shared codes in this research and freely available packages of R / RStudio in the Internet, besides the conventional exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) techniques. The items of the studied instrument can be subjected to parametric and non-parametric item response theory and classical test theory based rigors of scale purification, followed by differential item functioning exercise.

c. Reliability is unfortunately still reported primarily using the Cronbach's alpha in spite of the wealth of literature available to showcase its underestimation and availability of free software packages like *userfrinedlyscience* in R for instance, to measure the appropriate ordinal polychoric estimates. This undesirable state is partly due to lack of awareness about the developments in psychometrics and partly due to the complacency on the part of the research community to give up Cronbach alpha's estimation and reporting due the apparent ease and familiarity involved in its estimation. It is strongly recommended and hoped that through the R codes shared in this research, future research studies would estimate and report appropriate ordinal data based alternative reliability estimates along with estimation and reporting of the state of the art Network Psychometrics based Structural consistency reliability of psychological scales.

d. Electronic data collection through Google forms and sharing of their tinyURL links using WhatsApp can be an environment friendly, flexible approach of conducting cost effective research, saving the use of papers, the associated stationary resources and time. This recommended approach can complement the traditional means of physical data collection, especially when there is large physical distance between the geographical areas of data collection, shortage of time on the part of the subjects to participate in the study and when certain unforeseen contingencies like onset of pendemics emerge.

e. Workshops and orientation programs for faculty members and research scholars should be conducted in offline / online mode to build awareness on the advancements in the field of psychometrics and on the availability and usage of free packages of R/RStudio to conducted state of the art structural equation modeling based tool / model validation and estimate alternative reliability estimands. Such exercises can over the period of time can build a culture of estimating and reporting the correct estimnands of validity and reliability and rise the over all standard of Indian research in Psychometrics.

f. Research based social media platforms like Researchgate can be optimally utilized to stay in touch with the who's who of the field of self regulated learning like Barry Zimmerman and of the field of Network Psychometrics like Sacha Epskamp, by following their profiles and getting notified on the availability of their latest works to remain updated on the advancements happening in educational psychology and psychometrics in general.

g. A digital forum or platform like a dedicated Facebook group can be created with the sole intention of promoting and aiding researchers on the niche topic of measurement invariance testing of psychological tools and models in the Indian context.

5.7 Suggestions for Future Studies:

a. Since the revised integrative trait model is new, replication studies need to be conducted in multiple contexts and groups, like secondary, higher secondary and tertiary level students of Indian education system. Considering the cultural diversity of the country, independent studies to measure the validity of this model should be conducted with samples of larger size. Once the configural invariance of self regulated learning construct is established, research can be extended to prove its metric, scalar and strict invariance involving equivalence with respect to residual invariance as well. However, attainment of partial measurement invariance through the achievement of metric and scalar invariance will also be a significant milestone. The future studies can be longitudinal in nature from being cross-sectional, allowing drawing of relatively stable inferences owing to the enormisity of the data collected and the duration of time of measurement.

b. This study was conducted by considering engineering undergraduates of computer science and mechanical streams of second and third years only, which can be further extended to students of other streams of engineering and to students pursing other general and professional courses to test the generality of the factor structure of self regulated learning model across multiple disciplines.

c. Self regulated learning is found to be batch invariant in this study. But, with lesser known techniques, it was found to be measurement variant. Hence, further studies with respect to batch with higher sample sizes should be carried out to establish the result of this study firmly. In case of deviation, the evolution of self regulation as a psychological variable with maturity needs should be studied to identify the factors influencing its established five components of cognition, metacognition, motivation, behavior and emotion.

d. Also, the self regulated learning variables which are specific to the courses studied by the students at a given level or grade should be identified for inclusion into the revised integrative model for better estimation of this construct at a grade.

e. Future studies can explore the effectiveness of the model in reducing the drop out rate of the engineering institutions by conducting further person-based Latent profile analysis (LPA) studies on the admitted students and developing appropriate policies at the institutional level to arrest it, by taking the LPA codes and results of this study as reference.

f. Influence of other demographic factors like locality, type of management of the educational institutions on self regulated learning can be explored whose results can prove to be beneficial for framing effective policies for the design, implementation and promotion of self regulared learning in educational institutions.

g. Presently, the use of instruments with varying Likert scale to measure the different variables of the five components of self regulated learning is indeed a challenge to be overcome through robust psychometric tests. In this study, the instrument Metacognitive awareness inventory (MAI) by Schraw and Dannison (1994) was revised by converting the dichotomous responses to polychoric five point Likert scale responses, to study the new psychometric and bring the instrument on par with other polytomous instruments. Increase in the response categories improved the psychometric of the revised MAI scale. Similar studies can be conducted to revise the instruments of academic delay of gratification, intrinsic academic motivation, academic procrastination, future time perspective and academic emotional regulation questionnaire by converting them into seven point Likert scale. In this context, it is worth mentioning particularly about the typical and challenging nature of academic delay of gratification scale by Bembenutty and Karabenick (1996), where the subjects are offered to select a specific response based on two contrasting scenarios related to academics on a four point Likert scale involving Definitely Choose A =1, Probably Choose A=2, Probably Choose B=3 and Definitely Choose B=4. Validation through improvement in the psychometrics of these instruments, would lead to consistent measurement of self regulated learning construct, through an instrument in which all the items belonging to five components and their respective variables are measured uniformly on a seven point Likert scale since majority of items of self regulated learning are measured using MSLQ which is a seven point Likert scale. Such an exercise would enrich the overall psychometrics of self regulated learning instrument.

Consequently, the efficiency in the inferences drawn would also improve. The validation studies of the instruments can be carried out using the robust confirmatory factor analysis techniques of Network Psychometrics for ordinal data using WLSMV estimator.

h. As a rationale for the adequacy of final sample size at n=533 in research studies with Structural equation modeling (SEM) involving Confirmatory Factor Analysis (CFA), the criteria mentioned in the work of Wolf et al. (2013) was used in this study, with details mentioned below:

Table 5.3 Wolf et al. (2013) Criteria for Sampling Adequacy in SEM:

Criteria	**Details**	**Result**	**Remark on Sample Size**
Bias	Level of Significance be 0.05	0.05	Adequate
Power	0.8 or more	0.99999	Adequate
Solution Propriety	Larger the sample size, lower the error leading to model convergence	Model converged at n=311 itself	Adequate
Effect of Number of Factors	When a latent variable has three or more factors, the effect of sample size is plateaued	SRL has five component factors	Adequate
Effect of number of Indicators or Items	When the indicators are six or more per latent variable, the effect is plateaued	On average the 14 variables, had 4 indicators or items to keep the model complexity in check	Not Adequate

Effect of magnitude of factor loading	Models with factor loadings above 0.5 require smaller sample size for model convergence	13 out of 14 variables, had factor loading above 0.5	Adequate
Effect of magnitude of factor correlations	More the interrelationship between the factors, smaller the sample size	The interrelationship between the factors is very strong with coefficients ranging from 0.576 – 0.997	Adequate

It is suggested that the above mentioned criteria can be adopted as a good practice for determing the adequacy of sample size in studies involving SEM-CFA, by the Indian psychometrics research community.

5.8 Conclusion

Self regulated learning as a vital construct, emerged as the centre of attention in psychological research over the decades, soon after it was given a theoretical underpinning by Bandura in 1986. However, literature of the research work carried out on it clearly shows that it is fragmented in nature, involving the study of interrelationships the components of self regulated learning have with other closely related variables. The reason behind such a state of affairs is due to the lack of a comprehensive model which could empirically measure self regulated learning by bringing all its components and their respective variables together. The role of volition as a component of motivation is a recent disclosure in literature, along with a tool to measure the illusive emotional component of academic self regulation.

Identifying these apparent grey areas, the present research sought to develop a revised integrative trait model of self regulated learning among undergraduates belonging to engineering profession considering the intimate relationship this profession shares with the economy and growth of the nation at large. The developed model is found to be valid and most importantly measurement invariant with respect to gender, batch and stream. Two profiles of self regulated learning, high and low, were found to exist among the sample engineering undergraduate subjects. The statistical techniques employed in the development of this model are state of the art and it is earnestly hoped that the model on its further scrunity by the research community would prove to be robust enough in measuring and profiling self regulated learning construct comprehensively of subjects belongings to multiple disciplines, leading to the development of self regulated learning profile specific intervention programs for the promotion of this vital construct in the country ultimately contributing to its human resource and economic progress.

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Appendix A: Revised Integrative Trait Model of Self Regulated Learning (RITMSRL) Questionnaire

Name of the Student: ____

Branch: CSE / Mech. **Year:** IIndyr / IIIrdyr **Gender:** M / F

College: ______________________________________ **CGPA:** ________ / 10.0

Instruction: Dear Students, please read the statements provided below and choose the option that best describes you. There are no right and wrong answers. The scores generated from your responses will be used for research purpose. Your information will be kept strictly confidential. **Thank you** for your voluntary participation

. **SECTION – I**

Below statements describe certain academic scenarios you can find yourself into. Kindly tick the option best suited to you.

S.No.	Item Statement	Kindly Select any one of the options per item statement			
1	"Go to a party the night before a test in a course and study only if you have time, : Study first and party only if you have time.	**Definitely Choose A**	**Probably Choose A**	**Probably Choose B**	**Definitely Choose B**
2	A. Spend most of your time studying just the interesting material in this course even though it may mean not doing so well, **<u>Or</u>** B. Study all the material that is assigned to increase your	**Definitely Choose A**	**Probably Choose A**	**Probably Choose B**	**Definitely Choose B**

	chances of doing well in the course.				
3	Study for a course in a place with a lot of pleasant distractions even though it may mean not learning the material, : Study in a place where there are no distractions to increase the likelihood that you will learn the material.	**Definitely Choose A**	**Probably Choose A**	**Probably Choose B**	**Definitely Choose B**
4	Leave right after a class to do something you like even though it means possibly not understanding that material for the exam, : Stay after class to ask your instructor to clarify some material for an exam that you do not understand.	**Definitely Choose A**	**Probably Choose A**	**Probably Choose B**	**Definitely Choose B**
5	Select now an instructor for a course who is fun even though	**Definitely Choose A**	**Probably Choose A**	**Probably Choose B**	**Definitely Choose B**

	he/she does not do a good job covering the course material, Wait for an instructor for a course who is not much fun but who does a good job covering the course material.				

SECTION II

Below statements describe certain academic projects or assignments you are allotted. Kindly tick the option best suited to you.

S.No.	Item Statement	Kindly Select any one of the options per item statement				
1	I put off projects until the last minute.	Agree	Somewhat Agree	Neutral	Somewhat Disagree	Disagree
2	I know I should work on college work, but I just don't do it.	Agree	Somewhat Agree	Neutral	Somewhat Disagree	Disagree
3	I get distracted by other, more fun, things when I am supposed to work on college work.	Agree	Somewhat Agree	Neutral	Somewhat Disagree	Disagree
4	When given an assignment, I usually put it away and forget about it until it is almost due.	Agree	Somewhat Agree	Neutral	Somewhat Disagree	Disagree

SECTION III

Below statements describe academic tasks you are allotted. Kindly tick the option best suited to you.

S.No.	Item Statement	Kindly Select any one of the options per item statement				
1	I complete projects on time by making steady progress.	Very Uncharacteristic of me	Uncharacteristic of me	Neutral	Characteristic of me	Very Characteristic of me
2	am able to resist temptation when I know that there is work to be done.	Very Uncharacteristic of me	Uncharacteristic of me	Neutral	Characteristic of me	Very Characteristic of me
3	I meet my obligations to friends and authorities on time.	Very Uncharacteristic of me	Uncharacteristic of me	Neutral	Characteristic of me	Very Characteristic of me

SECTION IV

Below statements describe certain feelings you might experience in the class. Kindly tick the option best suited to you.

S.No.	Item Statement	Kindly Select any one of the options per item statement				
1	When I am afraid of an exam/test, I tell myself that there is always a second chance.	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
2	I try to suppress the anger and rage I feel in class.	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
3	When I feel bad because of the teacher's comments, I do not want others to see that.	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
4	If I'm sad because of poor grades, I comfort myself with the thought that study is not the most important thing in life.	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

5	I do not want others to see how disappointed I feel about my failures.	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
6	I try not to show how angry I am when the teacher is not fair.	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
7	When I feel bad about failing an exam, I tell myself that it is not so important to be the best.	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
8	When I am ashamed of bad grades, I remind myself that grades don't always reflect real knowledge.	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
9	I try to hide the anger I feel towards the teacher.	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
10	I reduce exam tension by reminding myself that there are more important things in	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

SECTION V

Below statements describe scenarios related to why you go to college. Kindly tick the option best suited to you.

S.No.	Item Statement	Kindly select any one option per item statement						
1	I go to college because eventually i enable me to enter the job mark field that I like.	Does not correspo nd at all	Correspon ds a little	Somewhat Corresponds	Corresponds moderately	Corresponds fairly	Corresponds a lot	Corresponds exactly
2	I go to college because this will h make a better choice regarding my orientation.	Does not correspo nd at all	Correspon ds a little	Somewhat Corresponds	Corresponds moderately	Corresponds fairly	Corresponds a lot	Corresponds exactly
3	I go to college because I believe that a few additional years of education will improve my competence as a worker.	Does not correspo nd at all	Correspon ds a little	Somewhat Corresponds	Corresponds moderately	Corresponds fairly	Corresponds a lot	Corresponds exactly
4	I got to college for the fact that when I succeed in college I feel important	Does not correspo nd at all	Correspon ds a little	Somewhat Corresponds	Corresponds moderately	Corresponds fairly	Corresponds a lot	Corresponds exactly
5	I go to college for the pleasure I experience when I discover new	Does not correspo	Correspon ds a little	Somewhat Corresponds	Corresponds moderately	Corresponds fairly	Corresponds a lot	Corresponds exactly

6	I go to college for the pleasure that I experience in broadening my knowledge about subjects which appeal to me.	Does not correspond at all	Corresponds a little	Somewhat Corresponds	Corresponds moderately	Corresponds fairly	Corresponds a lot	Corresponds exactly
7	I go to college in order to obtain a more prestigious job later on.	Does not correspond at all	Corresponds a little	Somewhat Corresponds	Corresponds moderately	Corresponds fairly	Corresponds a lot	Corresponds exactly
8	I go to college to prove myself that I am capable of completing my college degree.	Does not correspond at all	Corresponds a little	Somewhat Corresponds	Corresponds moderately	Corresponds fairly	Corresponds a lot	Corresponds exactly
9	I go to college because in order to have a better salary later on.	Does not correspond at all	Corresponds a little	Somewhat Corresponds	Corresponds moderately	Corresponds fairly	Corresponds a lot	Corresponds exactly
10	I go to college because I want to have "the good life" later on.	Does not correspond at all	Corresponds a little	Somewhat Corresponds	Corresponds moderately	Corresponds fairly	Corresponds a lot	Corresponds exactly

SECTION VI

Below statements describe academic experiences in the class you might come across. Kindly tick the option best suited to you.

S.No.	Item Statement	Kindly select any one option per item statement						
1	I'm confident I can understand the basic concepts taught in this course.	Not at all true of me	Not true of me	Somewhat untrue of me	Neutral	Somewhat true of me	True of me	Very true of me
2	I'm confident I can understand the most complex material presented by the instructor in this course.	Not at all true of me	Not true of me	Somewhat untrue of me	Neutral	Somewhat true of me	True of me	Very true of me
3	I'm confident I can do an excellent job on the assignments	Not at all true of me	Not true of me	Somewhat untrue of me	Neutral	Somewhat true of me	True of me	Very true of me

	and tests in this course.							
4	I expect to do well in this class.	Not at all true of me	Not true of me	Somewhat untrue of me	Neutral	Somewhat true of me	True of me	Very true of me
5	Considering the difficulty of this course, the teacher, and my skills, I think I will do well in this class.	Not at all true of me	Not true of me	Somewhat untrue of me	Neutral	Somewhat true of me	True of me	Very true of me
6	In a class like this, I prefer course material that really challenges me so I can learn new things.	Not at all true of me	Not true of me	Somewhat untrue of me	Neutral	Somewhat true of me	True of me	Very true of me

7	In a class like this, I prefer course material that arouses my curiosity, even if it is difficult to learn.	Not at all true of me	Not true of me	Somewhat untrue of me	Neutral	Somewhat true of me	True of me	Very true of me
8	The most satisfying thing for me in this course is trying to understand the content as thoroughly as possible.	Not at all true of me	Not true of me	Somewhat untrue of me	Neutral	Somewhat true of me	True of me	Very true of me
9	When I have the opportunity in this class, I choose course assignments that I	Not at all true of me	Not true of me	Somewhat untrue of me	Neutral	Somewhat true of me	True of me	Very true of me

	can learn from even if they don't guarantee agood grade.							
10	I am a very motivated person	Not at all true of me	Not true of me	Somewhat untrue of me	Neutral	Somewhat true of me	True of me	Very true of me
11	I usually study in a place where I car, concentrate on my course work.	Not at all true of me	Not true of me	Somewhat untrue of me	Neutral	Somewhat true of me	True of me	Very true of me
12	I make good use of my study time for this course.	Not at all true of me	Not true of me	Somewhat untrue of me	Neutral	Somewhat true of me	True of me	Very true of me
13	I have a regular place set aside for studying.	Not at all true of me	Not true of me	Somewhat untrue of me	Neutral	Somewhat true of me	True of me	Very true of me

14	I make sure I keep up with the weekly readings and assignmentsfor this course.	Not at all true of me	Not true of me	Somewhat untrue of me	Neutral	Somewhat true of me	True of me	Very true of me
15	When a theory, interpretation, or conclusion is presented in class or in the readings, I try to decide if there is good supporting evidence.	Not at all true of me	Not true of me	Somewhat untrue of me	Neutral	Somewhat true of me	True of me	Very true of me
16	I treat the course material as a starting point and try to develop my	Not at all true of me	Not true of me	Somewhat untrue of me	Neutral	Somewhat true of me	True of me	Very true of me

	own ideas about it.							
17	I try to play around with ideas of my own related to what I amlearning in a course.	Not at all true of me	Not true of me	Somewhat untrue of me	Neutral	Somewhat true of me	True of me	Very true of me
18	Whenever I read or hear an assertion or conclusion in a class, I think about possible alternatives.	Not at all true of me	Not true of me	Somewhat untrue of me	Neutral	Somewhat true of me	True of me	Very true of me
19	When I study the readings for a course, I outline the materialto	Not at all true of me	Not true of me	Somewhat untrue of me	Neutral	Somewhat true of me	True of me	Very true of me

	help me organize my thoughts.							
20	I pay a lot of attention to my feelings	Not at all true of me	Not true of me	Somewhat untrue of me	Neutral	Somewhat true of me	True of me	Very true of me
21	When I study for a course, I go through the readings and myclass notes and try to find the most important ideas.	Not at all true of me	Not true of me	Somewhat untrue of me	Neutral	Somewhat true of me	True of me	Very true of me
22	I make simple charts, diagrams, or tables to help	Not at all true of me	Not true of me	Somewhat untrue of me	Neutral	Somewhat true of me	True of me	Very true of me

	me organizecourse material.							
23	When I study for this course, I go over my class notes and make an outline of important concepts.	Not at all true of me	Not true of me	Somewhat untrue of me	Neutral	Somewhat true of me	True of me	Very true of me
24	I think about what I really need to learn before I begin a task.	Not at all true of me	Not true of me	Somewhat untrue of me	Neutral	Somewhat true of me	True of me	Very true of me
25	I set specific goals before I begin a task.	Not at all true of me	Not true of me	Somewhat untrue of me	Neutral	Somewhat true of me	True of me	Very true of me

26	I think of several ways to solve a problem and choose the best one.	Not at all true of me	Not true of me	Somewhat untrue of me	Neutral	Somewhat true of me	True of me	Very true of me
27	I ask myself if I have considered all options when solving a problem.	Not at all true of me	Not true of me	Somewhat untrue of me	Neutral	Somewhat true of me	True of me	Very true of me
28	I periodically review to help me understand	Not at all true of me	Not true of me	Somewhat untrue of me	Neutral	Somewhat true of me	True of me	Very true of me

	important relationship.							
29	I find myself analyzing the usefulness of strategies while I	Not at all true of me	Not true of me	Somewhat untrue of me	Neutral	Somewhat true of me	True of me	Very true of me
30	I can control my anger when I want to	Not at all true of me	Not true of me	Somewhat untrue of me	Neutral	Somewhat true of me	True of me	Very true of me

31	I ask myself questions about how well I am doing while learning something new.	Not at all true of me	Not true of me	Somewhat untrue of me	Neutral	Somewhat true of me	True of me	Very true of me
32	I know how well I did once I finish a test.	Not at all true of me	Not true of me	Somewhat untrue of me	Neutral	Somewhat true of me	True of me	Very true of me
33	I ask myself if there was an easier way to do things after I finish a task.	Not at all true of me	Not true of me	Somewhat untrue of me	Neutral	Somewhat true of me	True of me	Very true of me

34	I ask myself how well I accomplish my goals once I’m finished.	Not at all true of me	Not true of me	Somewhat untrue of me	Neutral	Somewhat true of me	True of me	Very true of me
35	I ask myself if I learned as much as I could have	Not at all true of me	Not true of me	Somewhat untrue of me	Neutral	Somewhat true of me	True of me	Very true of me”

APPENDIX B – AUTHORITY LETTER

LOVELY PROFESSIONAL UNIVERSITY

Transforming Education Transforming India

Lovely Institute of Education

Dated: ______________

To

____

____

____

AUTHORITY LETTER

Dear Sir/Madam

Mr./Ms. ______________________________________ is a bonafide student of __________________________ in Education Programme of this University under registration no. _______________ and pursuing research for completion of his/her dissertation. He/She may be allowed to consult your School/Institute/Library for collection of data. Your kind cooperation in this regard will be appreciated.

Thanking You

Yours Truly

Supervisor

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APPENDIX C - List of Publications and Paper Presentations

1. **Chakraborty, R.&Chechi, V.K. (2019).** Validation of the Revised Academic Procrastination Scale – Short Form in the Indian Context, Paper Presented at the International Conference on " Volatile Consumer Behaviour and Marketing", Mittal School of Business, Lovely Professional University, Phagwara, Punjab, April 19, 2019.
2. **Chakraborty, R.&Chechi, V.K. (2019).** Gender Sensitivity of Academic Delay of Gratification Scale Responses in Undergraduate Professional Courses Students from Indian Muslim Minority Community, *Asian Journal of Psychology and Education*, 52(2), ISSN:0971-2909, pp: 69 – 76.
3. **Chakraborty, R.&Chechi, V.K. (2019).** Validation of Zimbardo Time Perspective Inventory Short Form in the Indian Context, *International Journal of Science and Research*, ISSN:2319-7064, 8(7), pp: 565-570, doi:10.21275/ART20199500.
4. **Chakraborty, R.&Chechi, V.K. (2019).** Validation of the Parsimonious Factor Structure of Metacognitive Component of Self Regulated Learning in the Indian Context, Paper Presented at MHRD sponsored National Seminar, *Rethinking Education: Developing a Culture of Inclusive and Equitable Quality Education*, Guru Nanak Dev University, Amritsar, Punjab, India, from 12^{th} – 13^{th} August, 2019.
5. **Chakraborty, R.&Chechi, V.K. (2019).** Verification of Unidimenisonality of Academic Delay of Gratification Scale in the Indian Context, *International Journal of Engineering and Advanced Technology* (IJEAT), Vol. 8 (5C), ISSN: 2249 – 8958, pp:1319-1324, DOI: 10.35940/ijeat.E1188.0585C19.
6. **Chechi, V.K., Bhalla, J. &Chakraborty, R. (2019).** Cross Cultural Validation and Adaptation of the Parsimonious Version of Motivated Learning Strategies Questionnaire in the Indian Context, *International Journal of Advanced Science and Technology*, 28(16), ISSN: 2005-4238, pp. 50-90.

7. **Chakraborty, R. &Chechi, V. K. (2019).** Validation of Revised Academic Emotion Regulation Questionnaire (AERQ) in the Indian Context, *International Journal of Scientific & Technology Research*, 8(12), ISSN: 2277-8616, pp. 1203-1209.
8. **Chechi, V.K., Chakraborty, R. &Sadeeq, M. (2019).** Measurement of Delay of Gratification among Indian Students of Creative Courses, *History Research Journal*, 5(6), ISSN: 0976-5425, pp: 802-811.
9. **Chakraborty, R. &Chechi, V.K. (2019).** Analysis of the Psychometrics of Academic Delay of Gratification Scale without Item 4, *History Research Journal*, 5(5), ISSN: 0976-5425, pp: 1832-1847.
10. **Chakraborty, R. &Chechi, V. K. (2020).** Does Sample Size Influence the Factor Structure of a Construct: A Validation Study of Academic Delay of Gratification Scale, *TEST Engineering and Management*, 82(1), ISSN: 0193-4120, pp: 15075-15080.
11. **Chakraborty, R. &Chechi, V.K. (2020).** Cross Cultural Adaptation of Academic Emotion Regulation Questionnaire (AERQ) in the Indian Context, *International Journal of Psychosocial Rehabilitation*, (ISSN 1475-7192), 24(4), pp:3721-3733.
12. **Chakraborty, R.&Chechi, V.K. (2020).** Network Psychometrics Based Validation of Academic Emotional Regulation Questionnaire (AERQ), *International Journal of Future Generation Communication and Networking*, 13(2), pp:465-486, ISSN: 2233-7857.
13. **Chakraborty, R.&Chechi, V.K. (2020)**. Network Psychometrics Based Validation of Volitional Component of Self Regulated Learning and Estimation of its Polychoric Ordinal Omega Relaibility, *MuktShabd (UGC Care Journal)*, 9(6), ISSN: 2347-3150, pp: 5890-5909, doi: 09.0014.MSJ.2020.V9I6.0086781.105094.
14. **Chakraborty, R.&Chechi, V.K. (2020)**. Testing the Assumptions of Tau-Equivalence and Reliability Analysis in the Academic Emotion Regulation Questionnaire (AERQ) Subscales, *Journal of Critical Reviews*, 7(16), ISSN: 2394-5125, pp:1830-1838.

15. **Chechi, V.K., Chakraborty, R. & Lakhanpal, S. (2020)**. Validation of Academic Intrinsic Motivation Scale in the Indian Context, Eurpoean *Journal of Molecular and Clinical Medicine*, 7(7), pp:3250-3256.

16. **Chakraborty, R. & Chechi, V.K. (2020)**.Latent Profile Analysis (LPA) of Motivated Strategies for Learning Questionnaire (MSLQ) in the Indian Context, *International Journal of Future Generation Communication and Networking,* 13(3), pp:3487-3496, ISSN: 2233-7857.

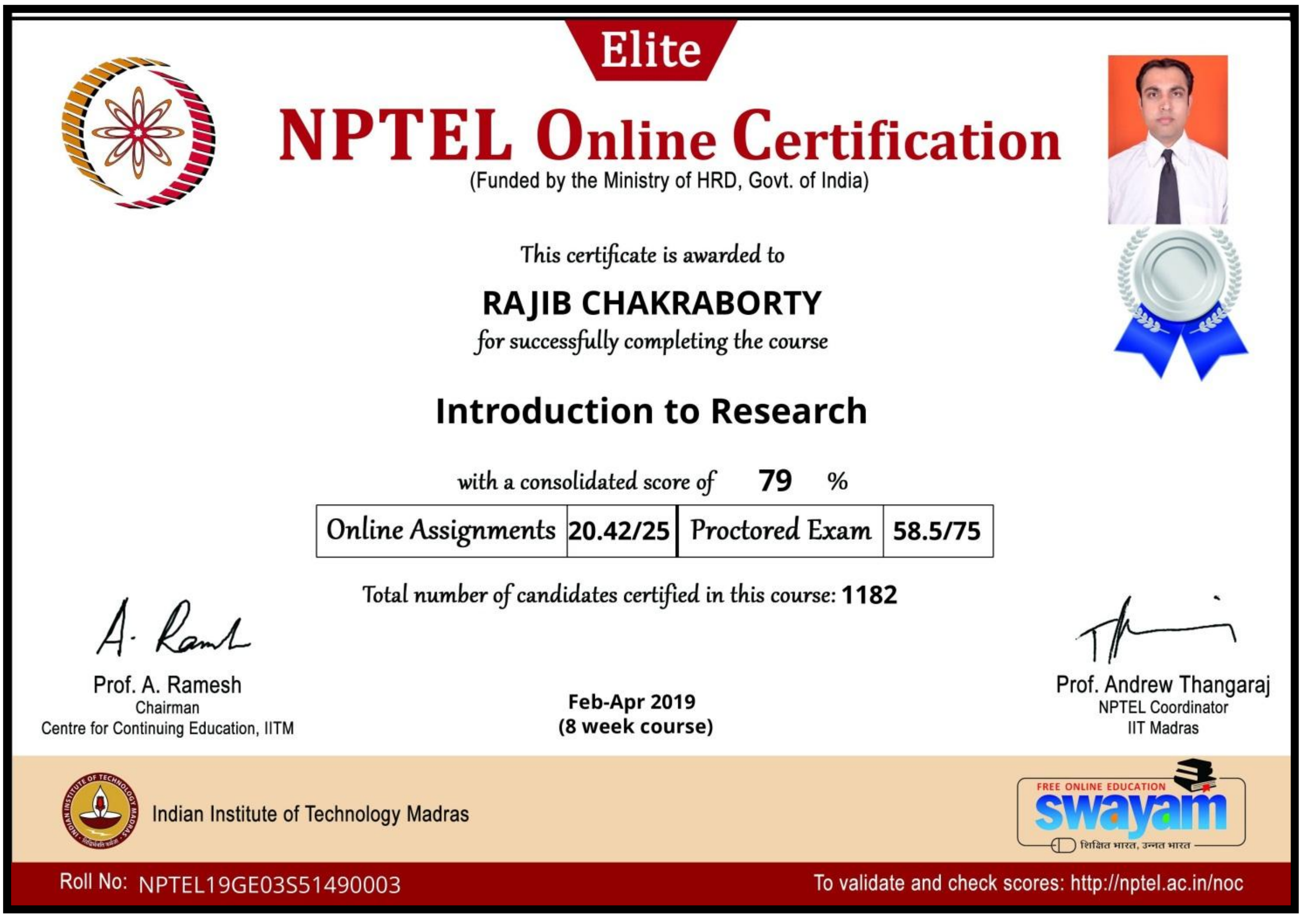
17. **Chakraborty, R. & Chechi, V.K. (2020)**. Structural consistency of psychological items – A harbinger communiqué in the Indian context, Paper presented in the National e-conference on *Education and Development:Post COVID-19,* on September, 2020, School of Education, Lovely Professional University, Punjab.

18. **Chakraborty, R. & Chechi, V.K. (2020)**.Ant Colony Optimization (ACO) Algorithm based scale purification of academic delay of gratification scale – A R/RStudio Tutorial, Paper presented in *5th International Multidisciplinary Research Conference (IMRC-2020),* Osmania University Centre for International Program, Osmania University Campus, Hyderabad, Telangana, India, 26th December, 2020.

19. **Chakraborty, R. & Chechi, V.K. (2021)**. Network Psychometrics Based Validation of Academic Delay of Gratification Scale Using Exploratory Graph Analysis (EGA) in R/RStudio, Paper Presented at *2 Days International Conference on Recent Innovations in Science, Engineering, Humanities and Management,* Institute of Engineers India (IEI), Sector 19A, Chandigarh, 16th-17th January, 2021.

20. **Chakraborty, R. & Chechi, V.K. (2021)**. Application of Network Psychometrics on Motivated Strategies for Learning Questionnaire (MSLQ), Paper Presented at *International Conference on Recent Innovation and Interdisciplinary Research (RIIR) - 2021*, International Association of Research and Developed Organization and All India Council for Productive Education, Research and Training, New Delhi, 13th February, 2021.

APPENDIX E – Online Certification -1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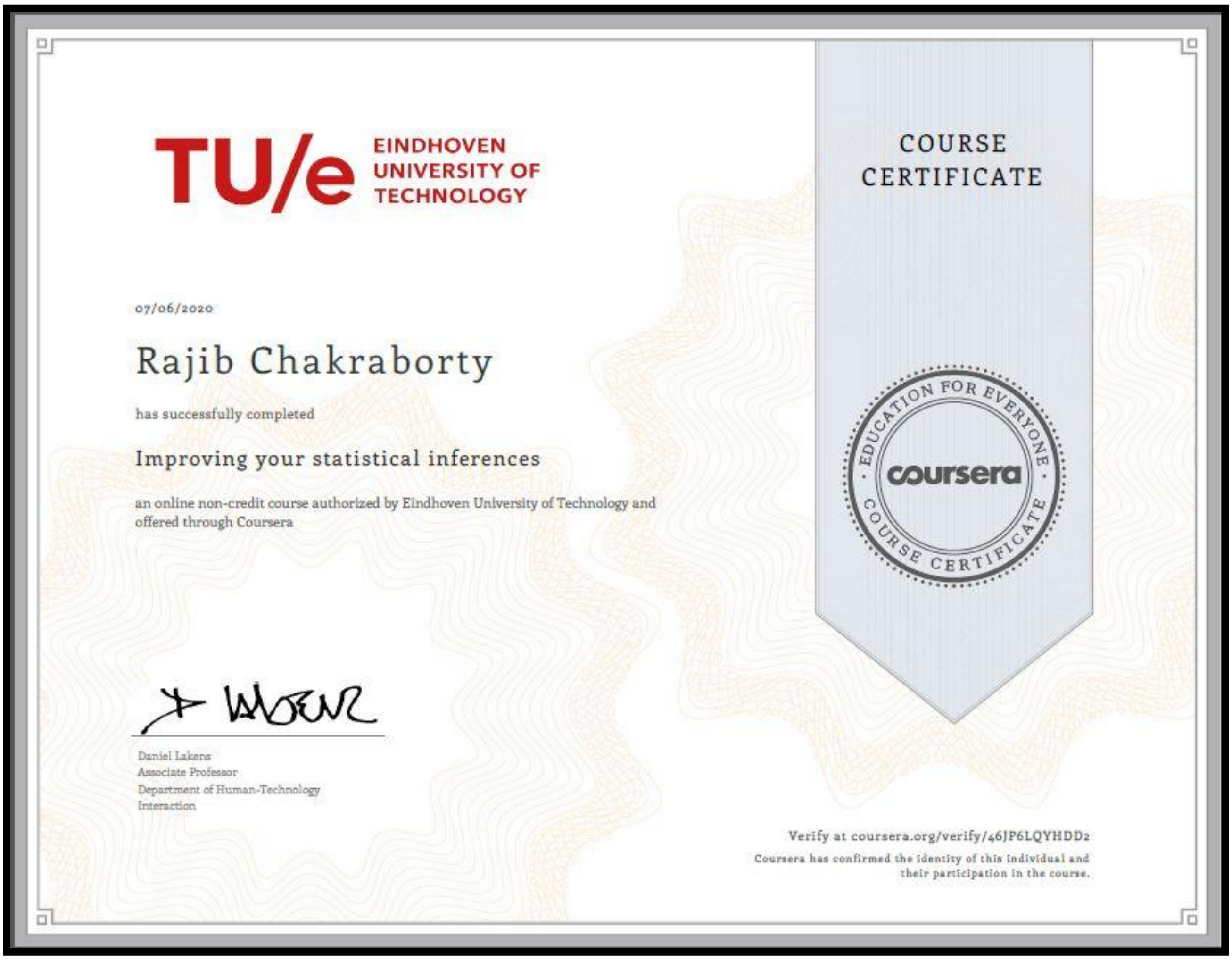

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