Academic Performance in Professional Programs is an Echo of Their Non-Cognitive Traits of Students: An Exploratory Study

Dr. Bhisaji C Surve
Assistant Professor,
SVKM's NMIMS
Mukesh Patel School of Technology Management & Engineering
Mumbai.
Email: bhisaji.surve@nmims.edu

Abstract:
In the recruitment process for jobs; the HR department conducts a series of tests and interviews to assess individuals' ability for job fit. Especially in fresher's selection; academic performance is taken as a criterion for candidate selection. The question is; does the percentage of marks or CGPA score of students reflects an individual's cognitive ability only or it also captures their non-cognitive skills too. As these non-cognitive skills are basically attitudinal characteristics of candidates so these measurable indicators can help HR to gauge students' attitudes to any extent. To answer this; the research is based on the "Theory of Planned Behaviour (TPB) "in which researchers consider the academic performance of Engineering students as long behaviour and they study about establishing causal impact of six Non-cognitive skills using PLS (Partial Least square) based Structural Equation Modelling. Results of PLS SEM model are discussed in detail with respect to validity and reliability.

Keywords: Theory of Planned Behaviour, Structural Equation Modelling, Non-cognitive skills, Measurement model, Construct validity, factor analysis.

Introduction:

The inspiration of this paper is derived from literature review published by "The Institute of Education" under the title "The impact of non-cognitive skills on outcomes for young people". This institute is under the University of London; the organization specialises in education and related areas of social science and professional practice. This literature review identifies major gap areas under the study for impact of non-cognitive skills. One of the concerns highlighted by this review; as even though there are enough evidences stating relationship between non-cognitive skills and outcomes of young students these studies are conducted in isolation and on short terms basis. The review insists as future studies are required to explore causalities of non-cognitive skills in the success and failures of young person's personal life objectives. Hence in this research; researchers have defined academic performance of students in engineering program as that objective which longitudinal one and involves standardized learning-evaluation processes with academic performance as measurable outcomes.

Student's academic performance is measurable through CGPA, as in engineering most of the university followed relative grading and it is cumulative figure consider over entire program this outcome is longitudinal and effective. Even though academic outcome in terms of CGPA is a measure of cognitive skills of students; researchers exploring a hypothesis as there is causal impact of non-cognitive skills on this academic performance over a period and to support this hypothesis researchers refer to "Theory of planned behaviour" stated by Icek Ajzen and B.L. Driver, 1992.

In order to establish causal relationship; researchers work on Structural Equation modelling with primary data captured through survey of Engineering Institute Alumni's from NMIMS University, Mumbai, India; those are passed out between 2015 to 2019. The research is based on data set from one engineering school only to ensure homogenous data and it ensure as educational processes variables like faculties, examination and evaluation format, general cognitive level of students, syllabus are required to be consistent so that causality impact can be uniformly established.

Researcher avoided data to capture after 2020 as the academic teaching-learning and evaluation process is mostly online and non-standard type; due to Covid-19 Pandemic leading to lock down in country. Final data set used from survey is of 275 responses after cleaning incomplete/erroneous responses.

Non-cognitive skill are the unique patterns of thought, behaviours, emotions which socially determined and developed over a period in life. The major non-cognitive skill lists out as self-perception of self-control, metacognitive strategies, social competencies, adaptability, motivation, perseverance, resilience and coping, as well as creativity (Gutman and Schoon 2013). Researchers focused on more flexible, malleable and impactful skills which are vital from student's perspectives. They have identified and restricted six vital non-cognitive skills which are essential for successful professional, family and social life; by doing literature survey and interacting with subject experts. Those are listed as below.

- **Self-efficacy** towards task refers to an individual's belief (conviction) that they can successfully achieve at a designated level on a task or attain a specific professional goal (Bandura, 1997; Eccles & Wigfield, 2002; Linnenbrink & Pintrich, 2002a).

- **Self-motivation** towards achievements is defined by" a student's desire (as reflected in approach, persistence, and level of interest) regarding professional subjects when the individual's competence is judged against a standard of performance or excellence (McClelland, et al., 1953)".
- **Anxiety** means "under test conditions, individuals has combination of physiological over-arousal, tension along with fear of failure, worry. (Zeidner M. (1998))".
- **Self-control** means" in order to achieve longer-term goal; it is the ability to subdue one's impulses, emotions, and behavior (Matt DeLisi (2014))".
- **Grit** is "the ability to persist in something you feel passionate about and persevere when you face obstacles. Person's passion and perseverance for long-term and meaningful goals (Duckworth, A.L.; Peterson, C.; Matthews, M.D.; Kelly, D.R. (June 2007))".
- **Conscientiousness** is "one of the Big five personality traits. Individuals who show an awareness of the impact that their own behavior has on those around them. (Costa, P. T. & McCrae, R. R. (1992).)".

The major research objectives:

1. How to incorporate assessment of non-cognitive skills in educational process along with formal cognitive skills assessments.
2. To establish causal relationship between non-cognitive skills and long-term endeavor which is academic performance throughout 4 years of engineering studies.
3. Out of six non-cognitive skills under studies which one has prominent impact on academic performance.

This work is extension of pilot work as explained in researcher's paper title of "Non cognitive constructs measurement model development based on Theory of Planned Behaviour (TPB) in context of Academic Performance of engineering students" published in "International Journal of Innovation and Learning", Dec 2021 under publication of InderScience Publishers.

Theory of Planned Behaviour:

The theory of reasoned action (TRA) is the first theory which state as the behaviour of individuals is predicted by the intention to perform that behaviour (Fishbein, 1980). The extension of TRA is "Theory of Planned Behaviour (TPB) "which was developed by Ajzen in 1985 and has been widely accepted. In social science, the causality of particular behaviour in human being is predictable as per TPB. According to this theory, human behaviour is a function of three predictors:

1. ATTITUDE 2. SUBJECTIVE NORMS 3. PERCIEVED BEHAVIORAL CONTROL

- Attitude define the individual's line of thinking towards the behavior. Everyone has his/her own belief which define the attitude of the person about the behavior.
- Subjective Norms consider what other think about the behavior; individual's behavior is to some extent shaped by what others think about your behavior where others mean mainly close one.
- Perceived behavioral control means individuals faith on his/her set of capabilities to meet the behavior.

These three factors ultimately define the Intention towards behaviour and this intension directly define individual's behaviour. Hence the TPB is a framework used by researcher in this paper to establish the model of causality by mapping various non-cognitive skills to respective components of TPB.

In this study there are three major constructs which are Attitude, Subjective Norms and Perceived Behavioural control which are further built on latent variables for each as **Attitude → Grit and Test Anxiety**, **Subjective Norms→ Conscientiousness** and finally **Perceived behavioural control → Self- Efficacy, Self-control** and **Academic Motivation.**

Mapping of respective six traits to Theory of Planned Behaviour (TPB) as a Measurement Model:

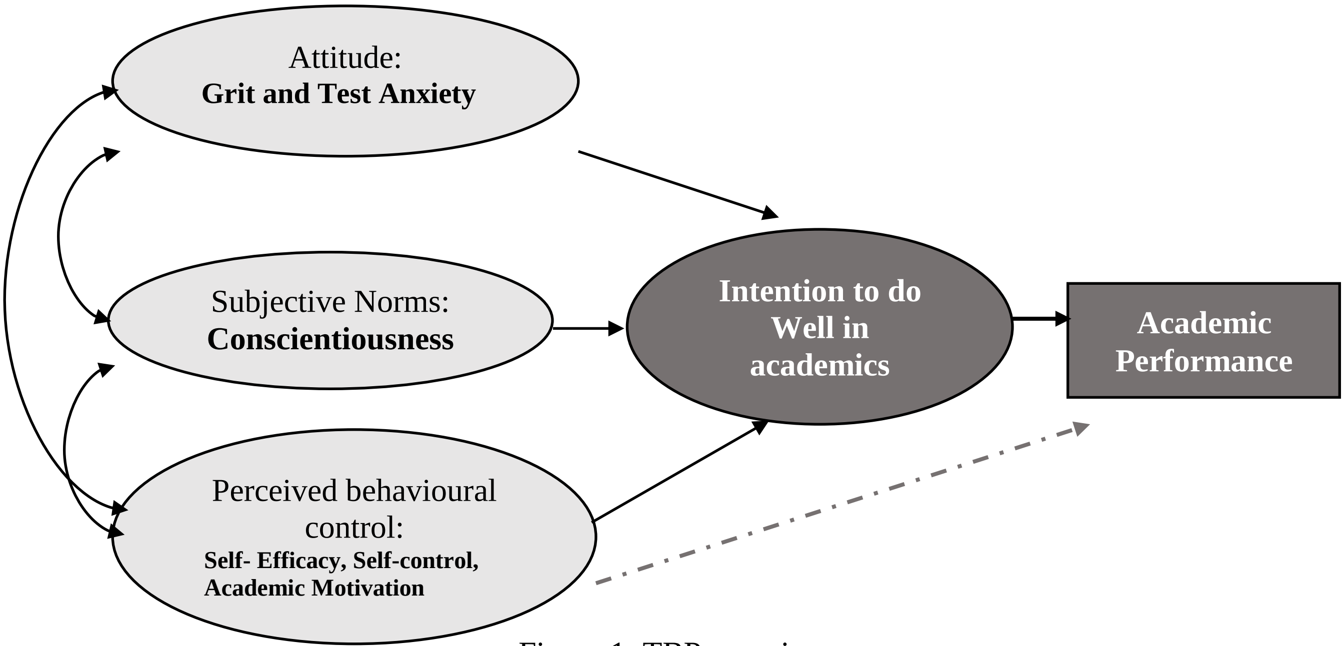


Figure 1: TBP mapping

Structural Equation modelling (SEM):

This is very useful technique in multivariate analysis, unlike other techniques which can give us either interdependence or dependence techniques but SEM gives a unique combination of both types. Operationally, SEM is combination of factor analysis and multiple regression analysis. It explains structure of interrelationships expressed in a series of equations similar to multiple regression equations. This is the only multivariate technique that allows the simultaneous estimation of multiple equations which represents the way constructs relate to measured indicator items as well as the way constructs are related to one another. As SEM allow the user to test a structural theory, it is very useful modelling in social sciences. SEM is also known as covariance structure analysis, latent variable analysis.

In this research, as researchers are interest to draw a causal inference i.e. causation. A causation inference involves a hypothesized cause and effect relationship between Non-cognitive skills and academic performance. Even though SEM alone cannot establish causality in totality but provide some evidences necessary support a causal inference. There are six major steps of SEM.

1. Defining individual constructs.
2. Developing the overall measurement model
3. Designing study to produce empirical results
4. Assessing the measurement model validity
5. Specifying the structural model.
6. Assessing structural model validity.

Stages of SEM implementation.

1. Defining individual constructs.

In this research context, there are six non-cognitive skills which are conceptual variables which are our independent variable and one is Academic performance which is directly measurable through CGPA which is dependent variable. Hence measurement of such variable is thorough defining a Latent variable which is also called as Construct and indirectly measured through observed variables which are set of questionnaires. Appendix I gives detail questions for each non cognitive skill measurement. All scales used in these measurements are from prior research and relative reference is stated in appendix.

2. Developing the overall measurement model

There are two types of constructs Reflective and Formative. In our research all our variables are Reflective nature. This means our constructs which are our respective skill is reflected as a response of the respondent on Likert scale for respective question. In other words, responses capture against respective question are considered to be caused by that construct. Even the directly measured variable Academic performance which reflect performance through CGPA in respective years of academic.

The important properties of Reflective constructs are:

- Causality from construct to Indicators

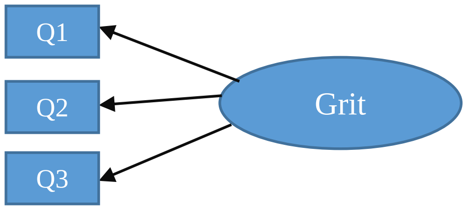


Figure 2: Reflective construct

- Internal Consistency: All items should possess internal consistency.
- Correlations: All items should be highly correlated.
- Measurement interchangeability: Removal of any item does not affect the original nature of the underlying construct.
- There is linear regression relationship between observed indicators and latent variable.

As stated earlier we have data set of 275 respondents which is used for model development. Researchers have already done factor analysis-based study on pilot data for survey questions for reduction and development of survey instrument more effective. This revised instrument is then deployed through own web site www.domysurvey.in to capture final primary data from respondent.

2.1 Statistical assessment of Primary data:

Kaiser-Meyer-Olkin (KMO) Test for Sampling Adequacy: KMO test results specify how is our data suitable for factor analysis; results criteria are as followed.

- 0.00 to 0.49 unacceptable; 0.50 to 0.59 miserable; 0.60 to 0.69 mediocre; 0.70 to 0.79 middling; 0.80 to 0.89 meritorious; 0.90 to 1.00 marvellous as per Kaiser.

Table 1: KMO test results for respective construct (IBM SPSS)

	SE	**SM**	**TA**	**SC**	**GR**	**CO**
KMO RESULT	0.784	0.776	0.683	0.808	0.734	0.683

SE: Self- efficacy **AM:** Academic- Motivation **TA**: Test Anxiety **SC**: Self- Control **GR**: Grit

CO: Conscientiousness

Bartlett's Test of Sphericity : This very useful test to make sure that the correlation matrix of the variables in our data diverges significantly from the identity matrix which ensure factor analysis work well with the dataset. It is observed as in Bartlett's test p-value for all construct is below 5% and hence it is suitable for factor analysis.

Factor analysis: Principal component analysis with varimax rotation is employed to check unique component identified in each construct and amount of variance explain by that component. We consider components having greater than 1 as Eigen value. Results for respective construct are as followed:

Table 2: Results of factor analysis as Total variance explained by each construct. (IBM SPSS)

CO: Conscientiousness

Total Variance Explained						
	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1.776	59.209	59.209	1.776	59.209	59.209

SE: Self- efficacy

Total Variance Explained						
	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.398	59.941	59.941	2.398	59.941	59.941

SC: Self- Control

Total Variance Explained						
	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.695	67.366	67.366	2.695	67.366	67.366

AM: Academic- Motivation

Total Variance Explained	
Component	Initial Eigenvalues	Extraction Sums of Squared Loadings

	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.570	64.246	64.246	2.570	64.246	64.246

TA: Test Anxiety

Total Variance Explained						
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1.942	64.722	64.722	1.942	64.722	64.722

GR: Grit

Total Variance Explained						
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.112	52.795	52.795	2.112	52.795	52.795

3. Designing study to produce empirical results

In this stage we need to address various issues which are related to Research design and Model Estimation.

3.1 Research design:

3.1.1 Covariance based or Correlation based: We are using variance-based modelling either Covariance-Based structural equation modelling (CB-SEM) or Partial Least Squares structural equation modelling (PLS-SEM).

3.1.2 Missing Data: Not Applicable in our dataset

3.1.3 Sample size: As per literature review by researchers; it is recommended as sample size is determine through power analysis (Hair et al., 2018; Hair et al., 2017; Hairet al., 2019; Kline, 2016; Ringle et al., 2018; Uttley, 2019). The minimum sample size can be determine using Power analysis which take into consideration the part of the model with highest number of predictors (Hair et al., 2014; Roldán & Sánchez-Franco, 2012).

In order to calculate the minimum required sample size; it requires information related to power, effect size, and significance level (Hair et al., 2018). A statistic's ability to correctly reject the null hypothesis when it is false can be explain by Power (1-β error probability) (Burns & Burns, 2008, p.

244). In context of social science research; value of 80 percent or more represents an adequate level of power (Cohen, 1988; Hair et al., 2017; Uttley, 2019). Hence researchers used G*Power software tool to estimate minimum sample size required; various setting under consideration of six predictors and power as 0.8 are as shown in figure 3.

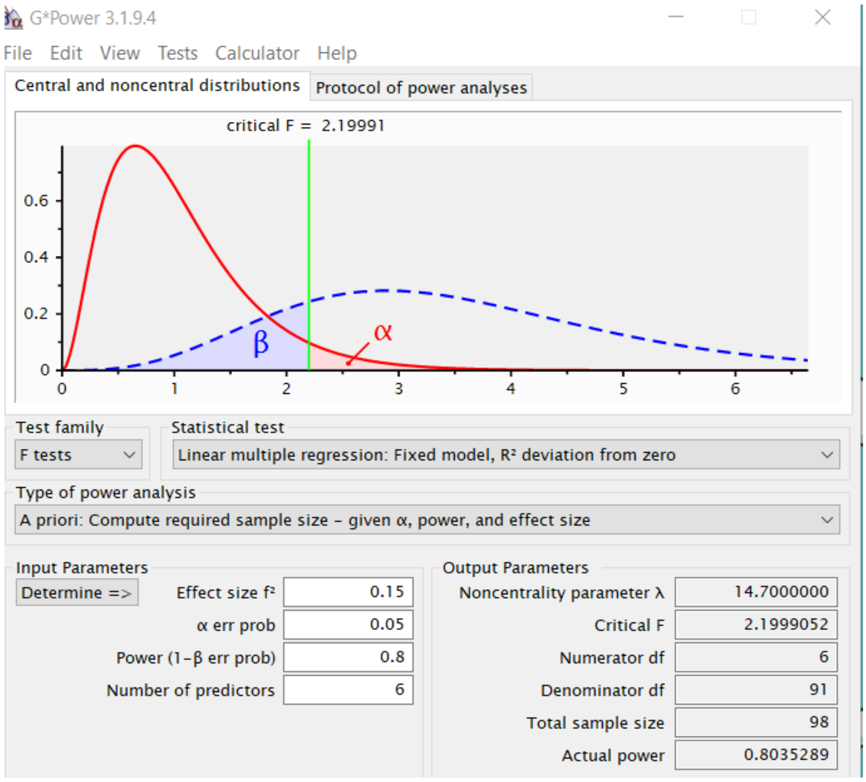


Figure 3: G Power sample size

But the sample size as obtained 98 is just minimum sample size; as a thumb rule we should use about 3 times minimum; so 275 is nearly suitable sample size in this research work.

Model Estimation

3.2.1 Model Structure: Researchers are using Theory of planned Behaviour as the theoretical model structure and accordingly path diagram is worked out. This is very important step in SEM analysis.

3.2.2 Estimation Techniques: This is about the mathematical algorithm use in estimation of various parameters by the model as explained below we are opting for Partial least square techniques(PLS). Computer software used: In order to implement and evaluate model; we are using PLS-SMART software.

Why PLS base SEM?

Once researchers identified Structural Equation Modelling (SEM) for establishing their theory; next task is to identify suitable methods in SEM. Prominently we have options as Covariance-Based structural equation modelling (CB-SEM) and Partial Least Squares structural equation modelling (PLS-SEM). Researchers have opted for PLS-SEM because:

- Context of research is testing a theoretical framework from a prediction perspective.
- Structural model is including many constructs, indicators and model relationships.
- It is exploratory research for theory development.
- It can give predictive modeling in which researchers are interested.
- Distribution of data is not a major concern with PLS method.
- It works well even with small sample size and large size as well.

Literature review in support of using PLS SEM is express herewith as:

The high degree of statistical power compared of PLS SEM to CB-SEM give researchers benefit (Reinartz et al., 2009; Hair et al., 2017b). PLS-SEM is more likely to identify relationships as significant when they are indeed present in the population when there is greater statistical power. (Sarstedt and Mooi, 2019).

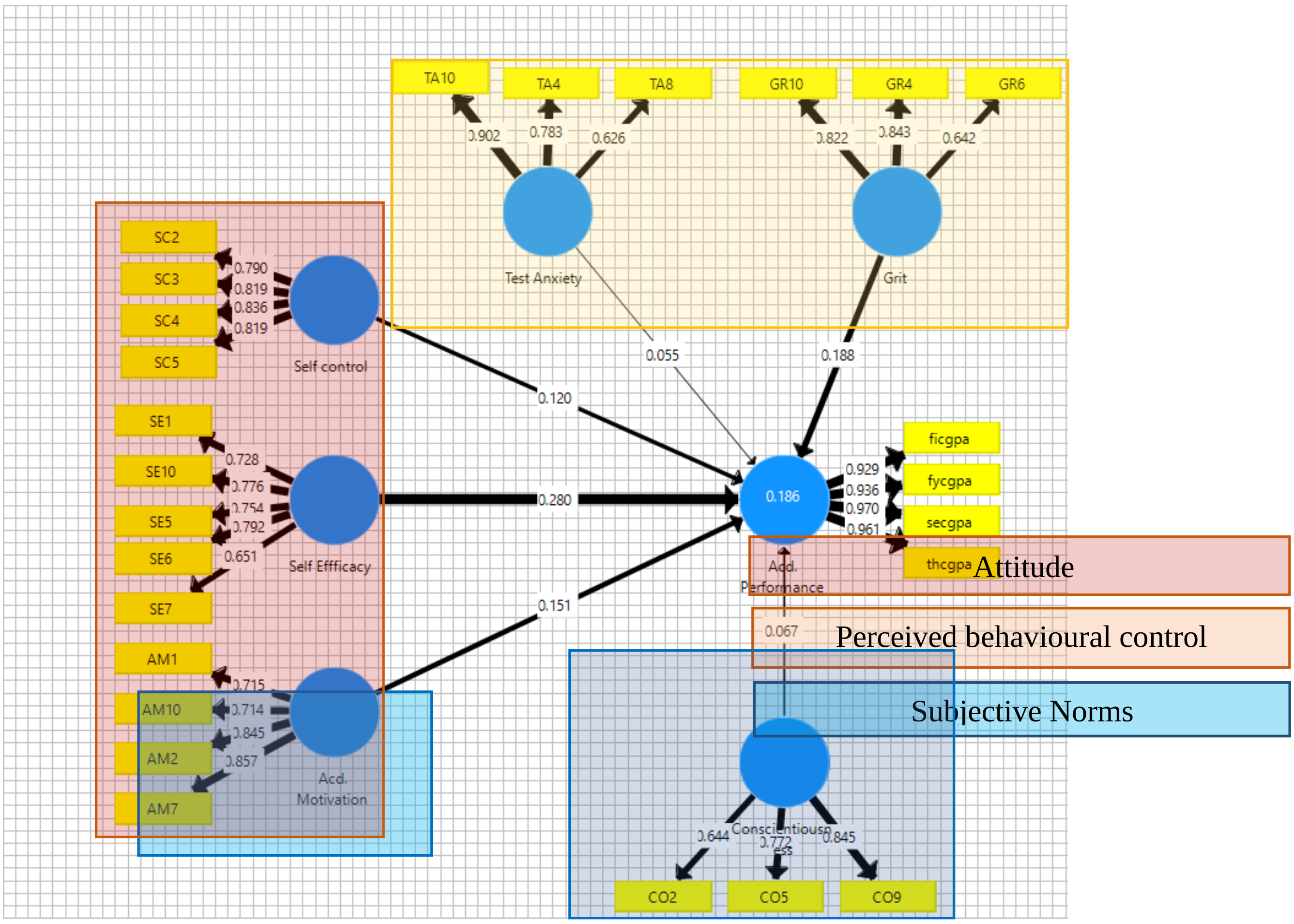
PLS structures are designed to provide causal explanations as it uses causal-predictive approach to SEM that emphasizes prediction in estimating statistical models (Wold, 1982; Sarstedt et al., 2017a).

This PLS based SEM provides both as exploratory analysis which is of major interest for academic reserachers as well as predictive analysis for managerial implications (Hair et al., 2019). This techniques employs both PCA Principal components analysis along with ordinary least squares regressions (Mateos Aparicio, 2011).

4. Assessing the measurement model validity

Assessing reflective measurement models; the first step in reflective measurement model assessment involves examining the indicator loadings. Loadings above 0.708 are recommended, as they indicate that the construct explains more than 50 per cent of the indicator’s variance, thus providing acceptable item reliability. Following is the implemented model in SMART-PLS software.

Figure 3: Model with TPB mapping as per figure 1



The second step is assessing internal consistency & reliability, most often using Jöreskog's (1971) composite reliability. Higher values generally indicate higher levels of reliability. For example, reliability values between 0.60 and 0.70 are considered "acceptable in exploratory research," values between 0.70 and 0.90 range from "satisfactory to good." Values of 0.95 and higher are problematic, as they indicate that the items are redundant, thereby reducing construct validity (Diamantopoulos et al., 2012; Drolet and Morrison, 2001). The results of our model are tabulated below.

Table 3: Construct Reliability and Validity

	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
Test Anxiety	0.73	0.79	0.82	0.61

Consciousness	0.65	0.72	0.80	0.58
Grit	0.70	0.76	0.80	0.51
Academic Motivation	0.81	0.91	0.87	0.62
Self-control	0.84	0.86	0.89	0.67
Self-efficacy	0.77	0.80	0.85	0.59

The important step is to check the convergent validity of each construct measure. Convergent validity is the extent to which the construct converges to explain the variance of its items. The metric used for evaluating a construct's convergent validity is the average variance extracted (AVE) for all items on each construct. An acceptable AVE is 0.50 or higher indicating that the construct explains at least 50 per cent of the variance of its items. Alternatively, Henseler et al. (2015) proposed the Heterotrait-Monotrait (HTMT) ratio of the correlations (Voorhees et al., 2016). The HTMT is defined as the mean value of the item correlations across constructs relative to the (geometric) mean of the average correlations for the items measuring the same construct. Discriminant validity problems are present when HTMT values are high. Henseler et al. (2015) propose a threshold value of 0.90.

Table 4: HTMT Discriminant validity

	Acd. performance	Test Anxiety	Consciousness	Grit	Acd. motivation	Self-control	Self-efficacy
Academic performance							
Test Anxiety	0.101						
Consciousness	0.108	0.317					
Grit	0.315	0.149	0.224				
Academic motivation	0.09	0.231	0.156	0.217			
Self- control	0.174	0.154	0.127	0.405	0.186		
Self -efficacy	0.27	0.184	0.105	0.218	0.262	0.081	

5. Specifying the structural model.

This step involves specifying the structural relationship between various constructs as per proposed theory model. It is the structural hypothesis of researchers. Each hypothesis represents a specific relationship that must be specified ref. figure of model. The path coefficients of respective endogenous latent variable in this research it is Academic performance and there are six exogenous variables which are various non-cognitive skills given in following table. The path coefficients expressing the causality effect.

Table 5: Path coefficient from independent variable to dependent variable.

	Academic performance
Test Anxiety	0.055
Consciousness	0.068
Grit	**0.188**
Academic motivation	**0.151**
Self control	0.120
Self efficacy	**0.280**

6. Assessing structural model validity.

Structural model coefficients for the relationships between the constructs are derived from estimating a series of regression equations. Before assessing the structural relationships, collinearity must be examined to make sure it does not bias the regression results. VIF (The Variance Inflation Factor) values above 5 are indicative of probable collinearity issues among the predictor constructs,

Table 6: The Variance Inflation Factor (VIF)

	Inner VIF
	Academic performance
Test Anxiety	1.077
Consciousness	1.057
Grit	1.198
Academic motivation	1.147
Self-control	1.156

Self-efficacy	1.107

When the measurement model assessment is satisfactory, the next step in evaluating PLS-SEM results is assessing the structural model. Standard assessment criteria, which should be considered, include the coefficient of determination (R^2), the blindfolding-based cross validated redundancy measure Q^2 , the statistical significance and relevance of the path coefficients.

As refereeing to figure 3 model diagram; it is observed as Academic Performance construct R^2 is 0.186(19%) which Evaluate the portion of variances of the endogenous variables, which is explained by the structural model.

Predictive Validity (Q^2) or Stone-Geisser indicator which state the accuracy of the adjusted model. $Q^2 > 0$ is the criteria as per HAIR et al. (2014).

Table 7: Predictive Validity (Q^2)

	SSO	SSE	Q^2 (=1-SSE/SSO)
Academic performance	1100	959.189	0.128
Test Anxiety	825	825	
Consciousness	825	825	
Grit	1100	1100	
Academic motivation	1100	1100	
Self-control	1100	1100	
Self-efficacy	1100	1100	

- **Bootstrapping results:**

PLS-SEM relies on a nonparametric bootstrap procedure (Efron and Tibshirani, 1986; Davison and Hinkley, 1997) to test the significance of estimated path coefficients in PLS-SEM.

Table 8: Path coefficient with statistical significance

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Acd. Motivation -> Acd.	0.151	0.154	0.081	1.872	**0.031**

Performance					
Conscientiousness -> Acd. Performance	0.067	0.08	0.066	1.02	**0.154**
Grit -> Acd. Performance	0.188	0.186	0.055	3.444	**0**
Self Effficacy -> Acd. Performance	0.28	0.284	0.051	5.469	**0**
Self control -> Acd. Performance	0.12	0.131	0.058	2.089	**0.018**
Test Anxiety -> Acd. Performance	0.055	0.06	0.071	0.778	**0.218**

Table 9: R^2 result for dependent variable is also statistically significant.

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Academic performance	**0.186**	0.223	0.041	4.493	0

7. **Observations and conclusions:**

Parameter	Observation	Requirement	Conclusion
Estimate of Loadings and Significance	Refer Table 8	Standardized loadings should have a value of at least 0.708 and an associated t-statistic above ± 1.96 to be significant for a two-tailed test at the 5% level (Hair, Ringle, & Sarstedt, 2011).	Conscientiousness and Test anxiety has not significant causal relationship for Academic Performance.
Composite Reliability (construct)	Refer Table 3	The reliability of the construct can be measured in two ways – Cronbach's alpha (α) and composite reliability (CR). The rule of thumb for both reliability criteria is they need to be above 0.70. (Hair et al., 2019).	All constructs meet the requirements for reliability except Consciousness is marginally low.
Average Variance	Refer Table	Convergent validity can be measured by the Average Variance Extracted	All constructs meet the requirements for

Extracted (AVE)	3	(AVE) which should be 0.5 or higher.	convergent validity.
Discriminant Validity – HTMT	Refer Table 4	Researchers can apply cut off scores such as 0.85 and 0.90 to interpret their HTMT results. (Henseler, Ringle, & Sarstedt, 2015).	All constructs meet the requirements for Discriminant validity.

- Confirmatory Composite Analysis (CCA) with Reflective Measurement Model.
- Confirmatory Composite Analysis (CCA) with Structural Model Assessment.

Parameter	Observation	Requirement	Conclusion
Evaluate structural model collinearity	Refer Table 6	Collinearity problems can also occur at lower VIF values of 3-5 (Mason and Perreault, 1991; Becker et al., 2015). Ideally, the VIF values should be close to 3 and lower.	All constructs meet the requirements for structural model collinearity.
Examine size and Significance of Path Coefficients	Refer Table 8	The path coefficients are standardized values that may range from +1 to −1. The closer the path coefficient values are to 0 the weaker they are in predicting dependent (endogenous) constructs, and the closer the values are to the absolute value of 1 the stronger they are in predicting dependent constructs.	Conscientiousness and Test anxiety construct are lower and hence they are weak predictors for Academic performance.
R^2 of Endogenous Variables (in-sample prediction)	Refer Table 9	For the area of social and behavioral sciences, R^2=2% is classified with a small effect, R^2=13% as a median effect and R^2=26% as a large effect (COHEN 1988).	R^2 value of 0.19(19%) is moderately good value and it has statistical significance too as P-value is nearly 0.

Predictive Relevance Q^2 by using blindfolding.	Refer Table 7	Q^2 is an assessment of out-of-sample predictive power. Q2 , values larger than zero are meaningful whereas values below 0 indicate a lack of predictive relevance.	Q^2 is 0.13 being positive there is out of sample predictive power in the model but it's low.

8. **Future scope**:

As per the key findings of literature review by reserachers at University of London; Non-cognitive skills are positively associated for various outcomes of young people. But there is no single prominent skill that predicts long term outcomes; actually key skills are inter related and need to be developed in combinations. Review stress future research needs in area of long term aspects of young one like professional academic performance. This paper taken engineering students as a data set for professional educational program. This studies should be extended out across various educational institutions and varying professional programs like medical sciences, management studies, law, finance, performing arts etc. Data obtained from various domain of education from respective institution should be studied in context of subset and super set by interesting set or taking union of the sets; to identify key skills and their direct impact on outcomes of young professionals.

Reserachers of the opinion as making universal model across university is of no practical use rather it should be customized to institution level and it will be useful for educators to develop their mentoring processes and also it will be useful to recruiters to have insight about type of student's class not simply on the basis of cognitive skills majorly aptitude but non-cognitive skills too which reflect their attitude.

Appendix I:

	Questioner used with Likert scale (1-5):	**Reference Instrument used**
Test Anxiety	1. When I take a test that is difficult, I feel defeated before I even start.	Jerrell C. Cassady, W. Holmes Finch, Using factor mixture modeling to identify dimensions of cognitive test anxiety, Learning and Individual Differences, Volume 41,2015, Pages 14-20,ISSN 1041-6080.

	2. I feel under a lot of pressure to get good grades on tests. 3. When I take a test, my nervousness causes me to make careless errors.	
Consciousness	Myself… 1. think of myself a lot. 2. constantly thinking about my reasons for doing things. 3. usually aware of my appearance.	Scheier, M. F., & Carver, C. S. . (2013) . Self-Consciousness Scale--(SCS-R) . Measurement Instrument Database for the Social Science.
Grit	1. I have been obsessed with a certain idea or project for a short time but later lost interest. 2. I have difficulty maintaining my focus on projects that take more than a few months to complete. 3. I often set a goal but later choose to purse a different one.	Duckworth, A.L, & Quinn, P.D. (2009). Development and validation of the Short Grit Scale (Grit-S). Journal of Personality Assessment, 91, 166-174.
Academic motivation	Why do you go to Engineering College? 1. Because I experience pleasure and satisfaction while learning new things. 2. Because I thing that a college education will help me better prepare for the career I have chosen.	Alivernini, F., & Lucidi, F. The Academic Motivation Scale: An Italian validation

	3. For the pleasure that is experience in broadening my knowledge about subjects which appeal to me. 4. Because my studies allow me to continue to learn about many things that interest me	
Self -control	1. I do not seem capable of making clear Plans for most problems that come up in my life. 2. The goals I achieve do not mean much to me. 3. I have learned that it is useless to make plans. 4. The standards I set for myself are unclear and make it hard for me to judge how I am doing on a task.	The Self-Control and Self-Management Scale (SCMS): Development of an Adaptive Self-Regulatory Coping Skills Instrument by Peter G. Mezo
Self -efficacy	I can, 1. Perform experiments independently. 2. Work with tools and use them to build things 3. Work with tools and use them to fix things. 4. Design new things. 5. Master the content in the engineering related courses.	Measuring Undergraduate Students' Engineering Self-Efficacy: A Validation Study Article in Journal of Engineering Education · April 2016.

References:

1. Ajzen, I. (1991) 'The theory of planned behavior', Organizational Behavior and Human Decision Processes, December, Vol. 50, pp.179–211, DOI: 10.1016/0749-5978(91)90020-T.
2. Ajzen, I. and Driver, B.L. (1992) 'Application of the theory of planned behavior to leisure choice, Article in Journal of Leisure Research, July.
3. Alivernini, F. and Lucidi, F. (2008) 'The academic motivation scale (AMS): factorial structure, invariance and validity in the Italian context', TPM, Winter, Vol. 15, No. 4, pp.211–220.
4. Arzenšek, A., Košmrlj, K. and Širca, N.T. (2018) 'Predicting young researcher's university-industry collaboration using theory of planned behavior', International Journal of Innovation and Learning, Vol. 24, No. 2, p.200.
5. Cassady, J.C. and Finch, W.H. (2015) 'Using factor mixture modeling to identify dimensions of cognitive test anxiety', Learning and Individual Differences Journal, Vol. 41, pp.14–20, Elsevier, Ball State University.
6. Costa, P.T. and McCrae, R.R. (1992) 'The five-factor model of personality and its relevance to personality disorders', Journal of Personality Disorders, Vol. 6, No. 4, pp.343–359.
7. Delisi, M. (2014) 'Foundation for a temperament-based theory of antisocial behavior and criminal justice system involvement', Journal of Criminal Justice, February, Vol. 42, No. 1, pp.10–25, Lowa State University, DOI: 10.1016/j.jcrimjus.2013.11.001.
8. Duckworth, A.L., Peterson, C., Matthews, M.D. and Kelly, D.R. (2007) 'Grit: perseverance and passion for long-term goals', Journal of Personality and Social Psychology, July, Vol. 92, No. 6, pp.1087–101, DOI: 10.1037/0022-3514.92.6.1087.
9. Eccles, J.S. and Wigfield, A. (2002) 'Motivational beliefs, values and goals', Annual Review of Psychology, February, Vol. 53, No. 1, pp.109–132, University of Mayland, DOI: 10.1146/annurev.psych.53.100901.135153.
10. Fishbein, M. and Ajzen, I. (1975) Belief, Attitude, Intentions and Behavior: An introduction to Theory and Research, Addison-Wesley.
11. Flammer, A. (2001) 'Self-efficacy', International Encyclopaedia of the Social & Behavioral Sciences, December, pp.13812–13815, University of Bern, DOI: 10.1016/B0-08-043076-7/01726-5.

12. García, E. (2016) 'The need to address non-cognitive skills in the education policy agenda', in Khine, M.S. and Areepattamannil, S. (Eds.): Non-cognitive Skills and Factors in Educational Attainment, Contemporary Approaches to Research in Learning Innovations, Sense Publishers, Rotterdam.
13. Gutman, L.M. and Schoon, I. (20113) 'The impact of non-cognitive skills on outcomes for young people', Literature Review, November, Institute of Education, London.
14. Hair, J.F., Black, W.C., Babin, B.J., Anderson, R.E. and Tatham, R.L. (2007) Multivariate Data Analysis, Pearson Publication, South Asia.
15. Lee, J. and Stankov, L. (2016) Non-cognitive Influences on Academic Achievement Evidence from PISA and TIMSS, Sense Publishers, Rotterdam.
16. Linnenbrink, E.A. and Pintrich, P.R. (2002) 'Motivation as an enabler for academic success', School Psychology Review, Vol. 31, No. 3, pp.313–327.
17. Lipnevich, A.A., Gjicali, K. and Krumm, S. (2016) 'Understanding attitudes in education', in Khine, M.S. and Areepattamannil, S. (Eds.): Non-cognitive Skills and Factors in Educational Attainment, Contemporary Approaches to Research in learning Innovations, Sense Publishers, Rotterdam.
18. Mamaril, N., Usher, E.L., Li, C., Ross, D. (2016) 'Measuring undergraduate students' engineering self-efficacy: a validation study', Article in Journal of Engineering Education, April, DOI: 10.1002/jee.
19. McClelland, D.C., Atkinson, J.W., Clark, R.W. and Lowell, E.L. (1953) The Achievement Motive, Appleton-Century-Crofts, New York.
20. Mezo, P.G. (2008) 'The self-control and self-management scale (SCMS): development of an adaptive self-regulatory coping skills instrument', Article in Journal of Psychopathology and Behavioral Assessment, Published online: 8 November 2008 # Springer Science + Business Media, LLC 2008; J. Psychopathol. Behav. Assess. (2009), Vol. 31, pp.83–93, DOI: 10.1007/s10862-008-9104-2
21. Neisser, U. (1996) Intelligence: Known & Unknown, February, Vol. 51, Emroy University, Published in American Psyhologist.

22. Pantrakool, S. and Chanchalor, S. (2018) ‘The relationship between emotional intelligence and the academic achievements of hearing impaired students in higher education in Thailand’, International Journal of Innovation and Learning, Vol. 23, No. 3, pp.353–367.

23. Petway, K.T., Brenneman, M.W. and Kyllonen, P.C. (2016) ‘Connecting noncognitive development to the educational pipeline’, in Khine, M.S. and Areepattamannil, S. (Eds.): Non-cognitive Skills and Factors in Educational Attainment, Contemporary Approaches to Research in learning Innovations, Sense Publishers, Rotterdam.

24. Poropat, A.E. (2009) ‘A meta-analysis of the five-factor model of personality and academic performance’, Psychological Bulletin, Vol. 135, No. 2, pp.322–338, https://doi.org/10.1037/a0014996.

25. Robbins, S.B. (2004) ‘Do psychosocial and study skill factors predict college outcomes? A meta-analysis’, Psychological Bulletin, April, Vol. 130, No. 2, pp.261–288, DOI: 10.1037/0033-2909.130.2.261

26. Sanchez-Ruiz, M.J., Khoury, J.E., Saadé, G. and Salkhanian, M. (2016) ‘Non-cognitive variables and academic achievement’, in Khine, M.S. and Areepattamannil, S. (Eds.): Non-cognitive Skills and Factors in Educational Attainment, Contemporary Approaches to Research in learning Innovations, Sense Publishers, Rotterdam.

27. Scheier, M.F. and Carver, C.S. (1985) ‘The self-consciousness scale: revised version for use with general populations’, Journal of Applied Psychology, Vol. 15, pp.687–699.

28. Seipp, B. (1991) ‘Anxiety and academic performance: a meta-analysis of findings’, Anxiety Research, June, Vol. 4, No. 1, pp.27–41, DOI: 10.1080/08917779108248762.

29. Surve, B.C. and Londhe, B.R. (2020) ‘Artificial Intelligence based assessment and development of student’s non-cognitive skill in professional education through online learning management system’, 2020 Fourth International Conference on Inventive Systems and Control (ICISC), Coimbatore, India, pp.329–336, DOI: 10.1109/ICISC47916.2020.9171137.

30. Surve B.C. and Londhe, B.R. (2021),“Non cognitive constructs measurement model development based on Theory of Planned Behaviour (TPB) in context of Academic Performance of engineering students” published in “International Journal of Innovation and Learning”, Dec 2021.

31. Zeidner, M. (1998) Test Anxiety: The State of the Art, Plenum Press, New York

32. Joe F. Hair Jr.a,⁎ , Matthew C. Howarda , Christian Nitzl 'Assessing measurement model quality in PLS-SEM using confirmatory composite analysis', Journal of Business Research, Volume 109, March 2020, Pages 101-110.

33. Leslie Morrison Gutman, Ingrid Schoon,' The impact of non-cognitive skills on outcomes for young people Literature review', https://www.researchgate.net/publication/350941337, University of London.

34. Mumtaz Ali Memon* 1 , Hiram Ting2 , Jun-Hwa Cheah3 , Ramayah Thurasamy4 Francis Chuah5 and Tat Huei Cham6, 'SAMPLE SIZE FOR SURVEY RESEARCH: REVIEW AND RECOMMENDATIONS', Journal of Applied Structural Equation Modeling: 4(2), i-xx, June 2020.

Book:

[1.] Joseph F. Hair,Jr, Kennesaw state University, William C. Black, Lausiana State University, Barry J.

[2.] Babin University of Southen Mississippi, Rolph E.Anderson,Drexel University, Ronald L. Tatham

[3.] ,Burke Inc., Book: " Multivariate Data Analysis ",Pearson publication,2007.

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