Academic Performance in Professional Programs is Reflection of Non-Cognitive Factors in Students; Predictive Analysis using PLS based Structural Equation Modeling.

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Abstract:

Students in their under-graduation programs are in an important stage of transition from being a raw student to qualified professional, especially those of who doing professional programs in engineering, management, medicine, legal, finance etc. Industry expects student outcomes in these programs as more holistic one which should meet both cognitive and non-cognitive factors in individuals. The assessment process in such programs not only captures students' cognitive ability but there are non-cognitive factors that also indirectly influence the academic performance of the students. This paper is a case study to explore how the academic performance of students has a hidden influence on non-cognitive constructs. It is a predictive analysis using PLS-SMART to deduct the predictive nature of those non-cognitive aspects with statistical validations.

Keywords: Structural Equation Modelling, Non-cognitive traits, Measurement model, Construct validity,factor analysis.

1. Introduction:

A critical Literature Review published by the University of Chicago consortium strongly advocates the impact of non-cognitive factors on the academic performance of students. ABET and other accreditation bodies emphasize outcome-based learnings for professional courses in which many Programme Outcomes highlight non-cognitive aspects. Educational policymakers have given due importance to holistic value-based education to develop our youth for a promising future.

James Heckman (2008), the Economist and Nobel laureate state that non-cognitive factors such as motivation, time management, and self-regulation are most critical for later life outcomes which mean professional achievements. Even though much research has demonstrated as college success and career readiness is not only dependent on content knowledge and core academic skill but Non-cognitive factors too. There is grey area about how different types of Non-cognitive factors play role in student academic success stories. Hence to address this unclear fact; researchers had a case study on PLS structural equation modelling based analysis to discover facts or statistical confirmation for the hypothesis.

In this paper; researchers explore a case study based on data captured from of Engineering Institute Alumni of NMIMS University, Mumbai, India which has ABET-accredited Engineering program; these Alumni are passed out between 2015 to 2019. The research is specific to the data set from one Engineering Institution only; to ensure homogenous data. As it ensures educational processes variables like faculties, Examination /Evaluation format, in general, cognitive level of students, syllabus etc. being consistent and do not contribute causality toward variance in academic performance and the impact of non-cognitive aspect can be uniformly established. Researchers avoided data to be captured after 2020 as the academic teaching-learning and evaluation process is mostly online and non-standard type; due to the Covid-19 Pandemic leading to lock down in the country. The final data set used from the survey is 275 responses after cleaning incomplete/erroneous responses.

Non-cognitive skill:

They are the unique patterns of thought, behaviors and emotions which socially determined and developed throughout 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 students' perspectives. They have identified and restricted six vital non-cognitive skills which are essential for successful professional, family and social life; by doing a literature survey and interacting with subject experts.

This research work is an extension of the paper presented by researchers in "International Conference on Inventive Systems and Control, the ICISC 2020, Scopus-Indexed IEEE Conference held at Coimbatore, India.". In which, it is proposed how Artificial Intelligence can incorporate into Learning management systems for assessment and development of non-cognitive skills in students. (Bhisaji and Dr. B. Londhe, 2020).

2. Literature review:

Literature Review published in June 2012 under the title "Teaching Adolescents to Become Learners" by the University of Chicago give the framework for this case study. This review identifies five general categories of non-cognitive factors related to academic performance: 1) Academic Behaviours, 2) Academic Perseverance, 3) Academic Mind-sets, 4) Learning strategies, and 5) Social Skills.

A Hypothesized Model of How Five Non-Cognitive Factors Affect Academic Performance within a Classroom/School and Larger Socio-Cultural Context is as followed.

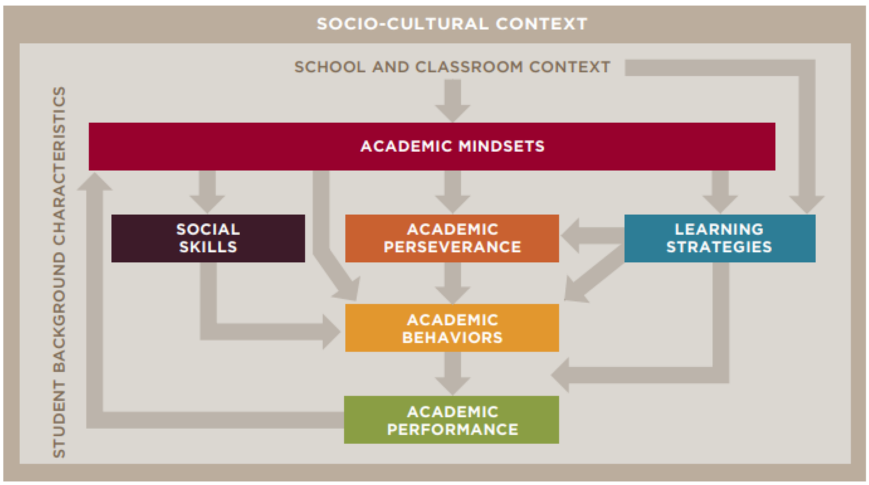


Figure 1:A Hypothesized Model of How Five Non-Cognitive Factors Affect Academic Performance. (courtesy : University of Chicago consortium)

Researchers identified six construct which are essential for successful professional, family and social life; by doing literature survey and interacting with subject experts. These respective constructs are mapped with respective factors as followed:

Non-Cognitive Factors	**Construct**
ACADEMIC MINDSET	Self-efficacy
ACADEMIC MINDSET	Self-motivation
ACADEMIC MINDSET	Test Anxiety
LEARNING STRATEGIES	Self-control
SOCIAL SKILLS	Conscientiousness
ACADEMIC PERSEVERANCE	Grit

Definitions of constructs:

- **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).
- **Test Anxiety** means under test conditions, individuals have 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).)

Why Engineering students as sample domain?

- It’s four years of long performance which gives longitudinal data in terms of time.
- Students are in the age group which can be consider as matured adults.
- CGPA score give relative and cumulative grading.
- Education process is standardized as ABET accredited.
- Students’ assessment is vigorous in terms of periodic quiz, assignments, lab examination, written examination, presentations, projects etc.

Why PLS base SEM?

Researchers identified Structural Equation Modelling (SEM) for establishing theory. Prominent options can be 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 modelling in which researchers are interested.
- Distribution of data is not a major concern with the PLS method.
- It works well even with small sample sizes and large sizes as well.

3. Research Methodology:

3.1 Defining individual constructs.

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

3.2The measurement model development and validation.

In our research, all our variables are Reflective in nature. This means our constructs which are our respective skill is reflected as a response of the respondent on the Likert scale for the respective question as per Annexure I. In other words, responses captured against respective questions are considered to be caused by that construct. Even the directly measured variable Academic performance reflects performance through CGPA in respective years of academic. Researchers have already done factor analysis-based study on pilot data for survey questions reduction and development of survey instrument more effective.

The measurement model development work based on pilot data is explained in detail through a research paper published in "International Journal on Innovation and Learning, Vol. 30, No. 4, 2021 by Inderscience Enterprises Ltd.". This revised instrument is then deployed through the self-developed website www.domysurvey.in to capture final primary data from respondents.

Table 1: **Construct Reliability and Validity**

	Cronbach's Alpha	**rho_A**	**Composite Reliability**	**Average Variance Extracted (AVE)**
Academic Motivation	0.81	0.91	0.87	0.62
Academic	0.96	0.97	0.97	0.90

Performance				
Conscientiousness	0.65	0.72	0.80	0.58
Grit	0.67	0.71	0.82	0.60
Self-Efficacy	0.80	0.83	0.86	0.55
Self-Control	0.84	0.86	0.89	0.67
Test Anxiety	0.73	0.79	0.82	0.61

Composite Reliability expresses the construct reliability in terms of internal consistency in scale items; a reasonable threshold value in social study research is 0.6 and higher while Cronbach's Alpha is also used for reliability measures with similar upper limits. Cronbach's alpha is a conservative measure that tends to underestimate reliability. Our results for all constructs as per Table 1 meet the criteria for Construct Reliability.

Average Variance Extracted (AVE): It is a measure of convergent validity of construct which means, how measuring items converge to represent the underlying construct and the statistically acceptable value for the same is 0.5 and higher. Convergent validity is also fulfilled by all constructs.

Table 2: **HTMT Discriminant validity**

	Academic Motivation	Academic Performance	Conscientiousness	Grit	Self-Efficacy	Self-control	Test Anxiety
Academic Motivation							
Academic Performance	0.09						
Conscientiousness	0.156	0.108					
Grit	0.164	0.367	0.202				
Self-Efficacy	0.277	0.308	0.094	0.262			
Self-Control	0.186	0.174	0.127	0.423	0.092		

Test Anxiety	0.231	0.101	0.317	0.12 3	0.178	0.154	

3.3 Discriminant Validity: It is established to ensure the distinctiveness of the constructs which means the constructs in the path model are conceptually not correlated, researchers should consider 0.85 as threshold for HTMT(Heterotrait-Monotrait)ratio (Henseler et al. 2015) and ideally all values should be less than threshold. Referring to Table 2 all constructs meet the criteria.

3.4 The overall structural model assessment.

3.4.1 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 values above 5 are indicative of probable collinearity issues among the predictor constructs, but 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.

Table 3: Variance Inflation Factor (VIF)

	Academic Performance
Academic Motivation	1.153
Conscientiousness	1.051
Grit	1.207
Self-Efficacy	1.125
Self-control	1.153
Test Anxiety	1.076

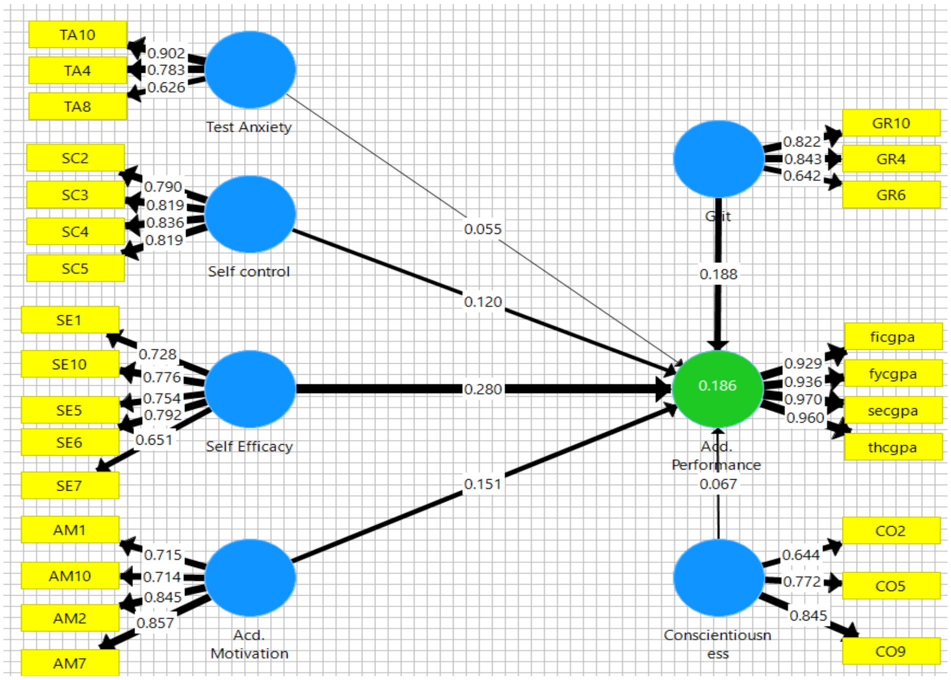


Figure 2: Structural model with loading, path coefficient and R^2

Measurement loadings are the standardized path weights connecting the factors to the indicator variables. In general, the larger the loading means a better and more reliable measurement model but ideally, path loadings should be above 0.7 (Henseler, Ringle, & Sarstedt, 2012: 269).

3.4.2Bootstrapping:

In bootstrapping, subsamples are created with observations randomly drawn (with replacement) from the original set of data. To ensure the stability of results, the number of subsamples should be large. Following is the result with a subsampling of 5000.

Table 4. Bootstrapping results

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Acd. Motivation -> Acd. Performance	**0.151**	0.153	0.082	1.841	0.033
Conscientiousness -> Acd. Performance	**0.067**	0.08	0.064	1.047	0.148
Grit -> Acd. Performance	**0.188**	0.185	0.053	3.562	0
Self Effficacy -> Acd. Performance	**0.28**	0.283	0.052	5.38	0
Self control -> Acd. Performance	**0.12**	0.131	0.056	2.148	0.016

Test Anxiety -> Acd. Performance	**0.055**	0.063	0.07	0.785	0.216

When the measurement model assessment is satisfactory, the next step in evaluating PLS-SEM results is assessing the structural model. It is observed as in Table 4 ; there are four causal relationship having statistical significance while Conscientiousness -> Acd. Performance and Test Anxiety -> Acd. Performance are statistically insignificant based on data set; even in these two cases the path coefficients are very low which signifies less causality.

It is observed as Self efficacy is major construct towards causality followed by Grit and Self-Control.

Standard assessment criteria, which is 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 2 model diagram; it is observed as Academic Performance construct R^2as 0.189(19%) to evaluate the portion of variances of the endogenous variables, which is explained by the structural model. 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).

The coefficient of determination (R^2), which assesses the in-sample model fit of the dependent constructs' composite scores, by using the model estimates to predict the case values of the total sample. The R^2 value, however, only assesses a model's explanatory power, but provides no indication of its out-of-sample predictive power in the sense of an ability to predict the values of new cases not included in this estimation process. Hence in order to do so, researcher employed PLSpredic as explain below.

3.4.3 Blindfolding:

This algorithm omits every n^{th} data point for the indicators for the selected endogenous by default n=7th and does "d" iterations. The cross-validated redundancy is estimated from the "d" iterations which are combined to compute a total estimate of$Q^{2.}$.There is a Q^2 value for each reflectively-modeled endogenous factor in the model. A Q^2 value above 0 indicates that the model is relevant to predicting that factor.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).The Q^2 value does not draw on holdout samples, but on single omitted and imputed data points. It is a combination of in-sample and out-of-sample prediction without clearly indicating whether the model has good explanatory fit.

Table 5: Predictive Validity (Q^2)

	SSO	SSE	Q^2 (=1-SSE/SSO)
Acd. Motivation	1100	1100	
Acd. Performance	1100	932.17	**0.153**
Conscientiousness	825	825	
Grit	825	825	
Self Efficacy	1375	1375	
Self Control	1100	1100	
Test Anxiety	825	825	

4 Predictive modelling using PLSpredic:

Shmueli et al. (2016) developed PLSpredict, a holdout-sample-based procedure that generates case-level predictions on an item or a construct level to gain the benefits of predictive model assessment in PLS-SEM. As per basic concept of supervised machine learning; we have training data set which is used to train model and there is testing data set which is also known as holdout samples. During training process model estimate its various parameters which mathematically express training data profile or nature of variance. Hold out data set is unused values during training but use for testing to predict the dependent variable.

In context of this research all six non-cognitive skills measured through Likert scale indirectly through set of questioners. These skills are specifically called as constructs are predictors and they can be used to predict academic performance which is indicated by CGPA.

In order to perform PLSpredict, researchers need to set certain parameters which are listed as:

- **The number of folds(K)**: As PLSpredict is based on the implementation of k-fold cross-validation, in which the entire dataset is divided into k-equally sized subsets. As shown in figure we have number of folds K=5 then the algorithm picks up K-1(4) subset for training subsequently leaving one subset for validation. It averages out the performance of training model by repeating given number of repetitions. Then it shifts validation data set from one of the previous training data and using previous hold out set for training; thus procedure repeated for K number of iterations.

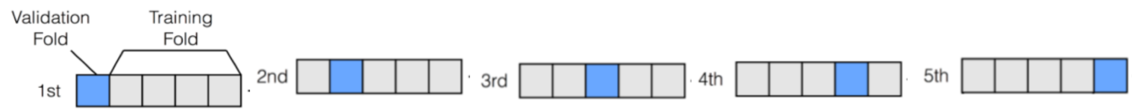


Fig 3. K=5-fold validation.

- **The number of repetitions (r) :** The number of repetitions specifies; with the set of data in each K-fold iteration how many time the algorithm repeat the training and errors measurements are average out after number of repetitions. Higher value of r will increase precisions but at the cost of more execution time.

- **Prediction statistic to measure the degree of prediction error**: In order to assess the model predictive power researchers, have to designate statistical parameters like the mean absolute error (MAE), the mean absolute percentage error (MAPE), and the root mean squared error (RMSE).

  The statistics are defined as follows where $\mathbf{y_i}$represents the value of y for observation i (i= 1,2,..., n) and $\mathbf{y_i}$ **cap** is the predicted value for that observation:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \qquad MAPE = \frac{1}{n}\sum_{i=1}^{n} \left|\frac{y_i - \hat{y}_i}{y_i}\right| \qquad RMSE = \sqrt{\frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{n}}$$

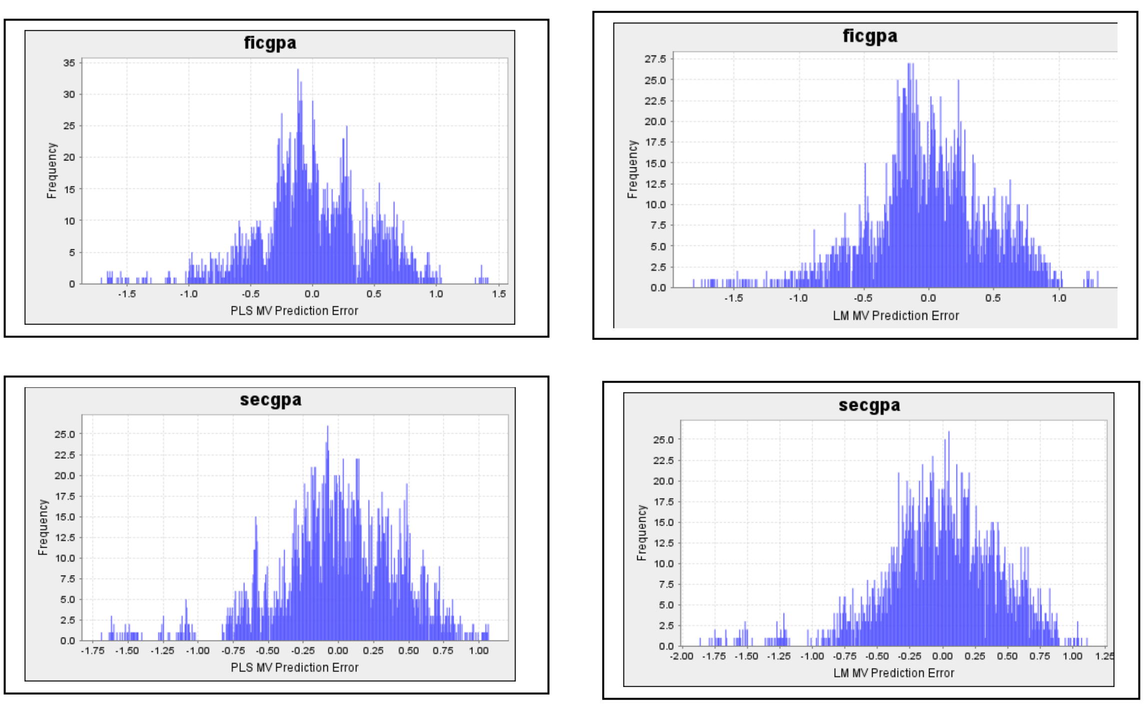
As indicated above formulae, mean absolute error(MAE) is useful to quantify the prediction error of the model. It is the average difference between the observed and predicted value by the prediction model. MAPE is more improvised version of MAR by using ratio term and hence it is independent from the manifest variable’s scale. The RMSE calculation the errors are square before averaging and hence it assign larger weights to larger errors, which is useful in the context when large errors are undesirable. The results show that the MAE and the RMSE reliably select models that best balance the model fit and the predictive power.

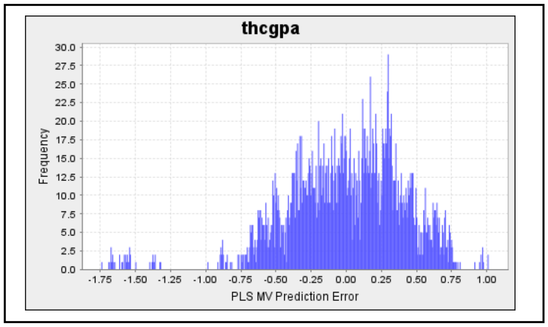
Sharma et al. (2019a) recently evaluated these three statistics’ and their related criteria’s efficacy in PLS-SEM-based model selection tasks. The results show that the MAE and the RMSE reliably select models that best balance the model fit and the predictive power.

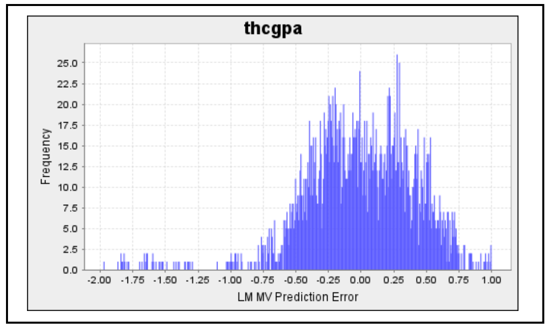
Table 6: Error comparison in absolute values for our model as per figure 2.

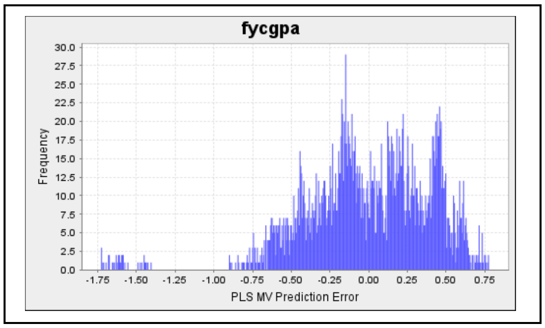
	PLS-SEM		**LM**		(PLS-SEM) - LM RMSE
Item	RMSE	Q^2_predict	RMSE	Q^2_predict	
First_yr_CGPA (ficgpa)	0.446	0.128	0.458	0.08	-0.012
Second _yr_CGPA (seccgpa)	0.427	0.132	0.437	0.092	-0.01
Third_yr_CGPA (thcgpa)	0.407	0.103	0.413	0.08	-0.006
Final_yr_CGPA (fycgpa)	0.4	0.09	0.41	0.047	-0.01

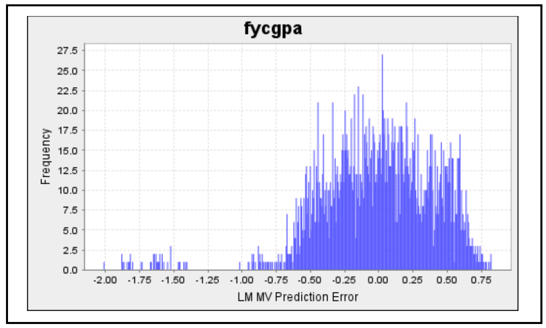
Figure 4 : Comparisons between PLS model and Linear Model(LM) error plot.











The visual inspection of above plots for the prediction errors suggests that the distribution is symmetric and follow normal distribution. Hence, we base our predictive power assessment on the RMSE values.Referring to above Table6; PLS-SEM error is less than LM for all indicators in terms of RMSE value which ensure as the model has high predictive power.

5. Conclusions and future scope:

Academic performance can be useful to understand underline Academic Behaviours, Academic Mind sets, Academic Perseverance and Learning strategies of students. In this era of technology. lifelong learning is a must especially for IT professionals. Hence non-cognitive factors are crucial for individual performance and hence mentoring students to improve these skills can enhance students' performance not only in academics but in their professional careers too.

On the other hand, the academically consistent performance of students is a useful predictor of students' attitude towards the assigned task. Artificial intelligence, machine learning and cloud computing can lead to machines that can acquire cognitive ability and content knowledge in near future but the attitude is pure humanly quality which is essential for good professionals and it is linked with Non-cognitive factors. There is still a lot of exploration required to learn about how to leverage non-cognitive aspects to transform educational practices which cultivate malleable Non-cognitive traits for the development of adolescents as good learners first and then good professionals.

At the respective institutional level even though authorities are aware of the importance of non-cognitive factors are so vital from a student's perspective; due importance to impart counselling and assessment in that respect is missing. Learning management system can be made more student interactive which can assess non-cognitive factors in students periodically and alert them to improve them which can bring in good insight for individuals to perform well in their academic as well as professional life.

Appendix I:

Non-cognitive skills	**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. 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.	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.
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. 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	Alivernini, F., & Lucidi, F. The Academic Motivation Scale: An Italian validation
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.	Measuring Undergraduate Students' Engineering Self-Efficacy: A Validation Study Article in Journal of

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