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Impact of Non-Cognitive Skills on Cognitive Learning Outcomes: A Study of Elementary Education in India

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IMPACT OF NON-COGNITIVE SKILLS ON COGNITIVE LEARNING OUTCOMES: A STUDY OF ELEMENTARY EDUCATION IN INDIA

Indrajit Bairagya∗ and Rohit Mukerji∗∗

Abstract

The significance of measuring non-cognitive skills of school children and understanding its importance in predicting academic performance is an area of research that has become increasingly prominent over the years. The objective of this paper is to measure the non-cognitive skills of students and also to examine its impact on the cognitive learning outcomes. Our methodology for constructing an index for non-cognitive skills is broadly divided into two parts. In the first part, eight sub-indices viz. consistency, perseverance of effort, growth mindset, conscientiousness, academic behaviour, self-regulated learning, self-control, school climate have been constructed for each of the aforementioned parameters using the technique of Polychoric-Principal Component Analysis. In the second stage, an overall index for non-cognitive skills has been constructed using these eight sub-indices. Further, cognitive learning outcomes have been measured on a test performed for the students of Standard IV on their mathematics competency. Results show that an overall non-cognitive skills index is a responsible factor behind a gloomy picture of Mathematics learning outcomes. Moreover, five indicators of non-cognitive skills, such as Perseverance of Effort, Growth Mindset, Conscientiousness, Academic Behaviour and Consistency show a significant positive correlation with the Mathematics test scores. Hence, an argument can be made for inculcating policy directives that aid in the development of non-cognitive skills and promote non-cognitive skills among children that shape their cognitive learning outcomes.

Introduction

Understanding the factors that tend to affect the 'academic performance' of a child has been a topic of constant research the world over for decades now, cutting across multiple disciplines. For economists, the dominant narrative around assessing the learning abilities of students has mostly focused on measuring their cognitive abilities, given that it has been found to have a strong influence in predicting labour market outcomes (Glewwe, Huang & Park 2017). However, analysing the effects of non-cognitive skills of students on academic performance involves studying its roots that are deeply entrenched in educational psychology. The progresses made over the past few decades in the fields of psychology and cognitive sciences have highlighted the flaws in restricting an individual's learning abilities to mere IQ tests that completely ignore the influence of one's immediate surroundings (Barsalou, 2010). Simultaneously, there has also been a plethora of literature recently that talks about the influence of non-cognitive 'skills' not only on the academic performance of a child in school, but also as a future predictor of outcomes in life (Gutman and Schoon, 2013). However, a wide range of 'skills', 'traits', 'beliefs' and 'behaviour' are brought together under the descriptor 'non-cognitive', making it difficult to measure or use it as a cogent input in evidence-based policy making or as a comparative tool across schools (Duckworth and Yeager, 2015). Hence, there exists a widespread inconsistency in the literature when it comes to defining succinctly the constituents of 'non-cognitive skills'. The fundamental flaw lies in the very segregation of cognitive and non-cognitive learning that inherently tries to denote a sense of

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detachment of the cognitive from the non-cognitive, creating an argument that is psychologically flawed.

There are multiple non-cognitive skills with a strong correlation with the academic performance of students (For a detailed literature survey, refer to Rosen *et al*, 2010; Farrington *et al*, 2012). Duckworth (2016) conducted a study of the public and local schools of Boston as part of understanding the relationship between student behaviour, non-cognitive skills and academic achievements. The non-cognitive skills that were measured included conscientiousness, grit, self-control and a growth mind-set. Growth mind-set and self-control were found to be strongly related to the test scores. In a different study, Duckworth and Seligman (2005) highlight the importance of self-control in respect of academic performance. Similarly, grit has also been found to be a strong predictor of academic performance among college students (Duckworth *et al*, 2007) and also of students graduating from high school. Gutman and Schoon (2013) identified eight non-cognitive skills having a positive correlation with academic performance. These included creativity, self-control, resilience and coping ability, motivation, meta-cognitive strategies, perseverance, self-perception of ability and social competencies. However, there are discrepancies observed in defining these skills individually that tend to overlap one another. In a cross-country study spanning 74 countries, the OECD PISA Survey (2012) included 'perseverance' as a measure of understanding students' learning of Mathematics. The results highlighted that students showing higher levels of perseverance had performed better in Mathematics. Other constructs of non-cognitive skills that have been found to be affecting the academic performance of students include academic behaviours, social skills, learning or meta-cognitive strategies and an academic mindset (Farrigton *et al*, 2012). Rosen *et al* (2010) also highlight the importance of 'motivation' as a non-cognitive skill and its role in students' academic achievements.

The question regarding an accurate measurement of these skills is also extended to the reliability and consistency of the data collected. Studies highlight two primary methods that have been used in measuring non-cognitive skills, namely through questionnaires or performance tasks (Duckworth and Yeager, 2015). While questionnaires are either filled in by teachers or are self-reported by the students themselves, performance tasks are particular experiments organised by researchers in controlled settings to understand the particular skills of the students. Administering self-report questionnaires often suffer from "reference" or "desirability" biases (Duckworth, 2016). Given the limitations of each method, Duckworth and Yeager (2015) stress the importance of maintaining caution before using measurements from non-cognitive skills as a tool for policy evaluations or inter-school comparisons.

Like in most other developing countries, studies measuring non-cognitive skills in India are significantly fewer compared to its cognitive counterparts. There have been studies that have focused on particular non-cognitive skills and assessed their impact in a school setting. For instance, Prayag Mehta's (1969) work on analysing the achievement motives of high school boys in Delhi. However, studies that compositely measure multiple non-cognitive skills collectively are few and far between. In a more recent work, Krishnan and Krutikova (2013) designed a quasi-experimental study that analysed the impact of an NGO in raising self-efficacy and self-esteem among students in Mumbai. Their study shows that external interventions can be effective in raising the non-cognitive skills of students.

Our study focuses on measuring the impact of non-cognitive factors on Standard IV students' cognitive (Mathematics) learning outcomes based on a primary survey conducted across 256 students studying in Standard IV across 40 schools in Karnataka, India.

The paper is organised as follows. The first section explains our methodological approach, detailing the sampling, non-cognitive factors that shall be measured and the methodology used to design and analyse them. Thereafter, we explain our cognitive assessment tool that seeks to measure the Mathematics learning of students. It is followed by our results and findings that draw comparisons between the test scores and their relationship to non-cognitive factors. The paper ends with our concluding remarks.

Methodology

Sampling

The existing large-scale surveys in India that measure learning outcomes of students focus on providing levels and do not furnish the exact scores achieved by students. Moreover, they do not include any questions to assess the non-cognitive skills of the students. Therefore, a primary survey has been carried out across different schools in Karnataka administering a new assessment tool that tests Standard IV students on their Mathematics learning and non-cognitive skills. The schools were selected based on a multi-stage stratified sampling. As first stage units (FSU), we chose two districts in Karnataka, one being urban and the other rural. The ultimate stage units (USU) were schools and students. A total of 40 schools (i.e., 20 schools from each district) have been selected as the ultimate stage units.

Assessment tool of learning outcome of Mathematics

While the National Achievement Survey assesses the learning outcomes of students in Standard V, the QES focuses on Standard IV students. It is also a grade level performance-based test, similar to our study. Since both of the studies are based on the syllabus prescribed by the NCERT, the concepts being tested by our study as well as the QES are similar. The key concepts that are being tested by our study include Basic Arithmetic Operations, Concept of Fractions, Shape Identification in Geometry, Concepts of Time and Money, Measurement, Number System and Pattern Identification. The total number of questions administered by our study is 21. The concept Pattern Identification has been added to our study that aims to analyse the ability of students to identify patterns and sequences irrespective of a particular mathematical concept.

Measuring Non-Cognitive Learning

The students were provided with self-report questionnaires in Kannada (their native language) that aimed to test seven essential non-cognitive skills and the school climate. These were selected based on our survey of literature where these skills were found to have strong correlations in predicting academic performance. There is also comparatively less debate in literature regarding the methodologies adopted to measure these skills. The skills that have been selected include a) Grit b) Growth Mindset c)

Conscientiousness d) Academic Behaviour e) Self-Regulated Learning f) Self Control g) Consistency. All the items measuring these skills in the questionnaire were based on a Likert scale, where the students were asked to rate themselves based on their perception of their performance in particular tasks and activities. The questions administered were descriptive in nature, highlighting particular situations faced by the students in their day-to-day academic learning in schools. These situations are contextually different in India than in other countries. Hence, the nature of the questions were altered accordingly.

For instance, Grit, as defined by Duckworth *et al* (2007), is the sustained long-term effort to achieve one's goals. For measuring it, we modified the Short Grit Scale created by Duckworth and Quinn (2009) and administered it to the students. The students answered through a Likert scale with 5 categories where 1 was rated as "Strongly Disagree".

Growth Mindset was defined similarly to the definition provided by Blackwell, Trzesniewski, and Dweck (2007) and the questionnaire was modified to the socio-economic context of India. These were also answered by the students using a 5 category Likert scale similar to Grit. An item on understanding the effect of caste on the growth mindset of students was also included (Eg.1. My future success depends on which caste I belong to).

The measure on Conscientiousness was adopted from the "Big Five" Personality Test created by John and Srivastava (1999) and was modified for administering to Indian students. Consistency as a measure aimed at understanding the levels of interest that the student maintains on a particular task/hobby and how often does he or she get distracted from the same.

The measure on Academic Behaviour is primarily based on sub-factors mentioned by Farrington *et al* (2012) and these were also endorsed by students using a 5-category Likert scale. While there are broadly three components in what constitutes as Self-Regulated learning, (see Pintrich and De Groot 1990 for more details) our study has mainly focused on Zimmerman and Pons (1986) definition of self-regulated learning that aims to understand how the students are able to grasp the material taught in school and understand the self-regulated learning strategies they employ. We have also referred to the MSLQ developed by Pintrich and De Groot (1990) to study self-regulated learning. Correspondingly, we have modified it according to the context of our study.

Our measure on self-control is based on the definition provided by Tsukayama, Duckworth, and Kim (2013). The domains we have considered are mainly related to 'task performance' and 'impulse control' as we aim to measure the relationship between the academic performance of students and self-control. We have combined the scales by Tangney *et al* (2004) and Duckworth (2016) to measure self-control and created a school context specific scale. Lastly, 'school climate' has been measured based on students' perceptions about teachers as well as the overall atmosphere in the classroom.

Table 1: Sample Questions for Measuring Non-Cognitive Skills

Non-Cognitive Skill	Items
Grit	1. I like to study on the day before the exam rather than study every day. 2. I work harder on the subject in which I had scored poorly.
Growth Mindset	1. My future success depends on whether I take private tuitions or not. 2. My future success depends on whether I am from an English Medium school
Conscientiousness	1. I often get distracted and end up watching TV or talking to friends when I sit to study. 2. I sometimes feel lazy while doing my school tasks.
Academic Behaviour	1. I arrive to class on time. 2. I remember to bring my books, copies, pen and other material needed for classes.
Self-Regulated Learning	1. Do you say the points over and over to remember better? 2. Do you highlight in your book with a pen/pencil when you study to remember the important points?
Consistency	1. I focus very hard on a particular task for a few days but leave it incomplete because I lose interest. 2. My hobbies and interests keep on changing from time to time.
Self-Control	1. I interrupt my friends when they speak in class and do not let them finish. 2. I sometimes do not revise my exam paper before submitting since I want to be the fastest to submit.

Constructing index for non-cognitive skills

The Principal Component Analysis (PCA) technique has been used to construct an index for non-cognitive skills based on eight broad parameters viz. consistency, perseverance of effort, growth mindset, conscientiousness, academic behaviour, self-regulated learning, self-control and school climate. Our methodology for constructing an index for non-cognitive skills is broadly divided into two parts. In the first part, eight sub-indices have been constructed for each of the aforementioned parameters. A separate set of questions have been asked related to each of the parameters and these questions are considered as variables to construct sub-indices. Since the questions asked related to each of the parameters are in Likert scale, the Pearson correlation may lead to an erroneous result as it assumes all variables normally distributed. To overcome this problem, polychoric correlation has been used to construct PCA-based sub-indices for the aforementioned eight parameters considering the fact that polychoric correlation does not assume the normal distribution of the variables. In fact, polychoric correlation considers the ordinal measurements of the variables. PCA tremendously reduces the number of variables and principal components are arranged based on their importance to explaining the original variables. Principal component scores represent the linear combination of the original variables. We have considered the first principal component scores related to each of the parameters as a representative of the sub-indices. In the second stage, an overall index for non-cognitive skills has been constructed using these eight sub-indices. The values of the sub-indices are continuous variables and normally distributed. In order to provide equal importance to each of the sub-indices, we have converted their values into normalised form. Although polychoric PCA technique has been used to construct sub-indices, a PCA based on Pearson correlation has been used to construct the overall index for non-cognitive skills. Again, we have considered the first principal component scores as a representative of the overall index for non-cognitive skills.

Measuring learning outcomes of Mathematics

To prepare the test papers to assess cognitive learning outcomes for the study, we have looked into the four major educational surveys that have been critiqued earlier i.e., The ASER Survey; IHDS Survey; Quality Education Report Survey (QES) (conducted by EI); and the National Achievement Survey (NAS). The assessment tools used by these surveys vary from each other as their objectives are different. For instance, while the ASER survey aims to test children aged between 5-16 years on their foundational abilities of reading and performing basic arithmetic, the National Achievement Survey focuses on assessing the grade-level performance of individuals. While the lacunae existing in these aforementioned surveys have been discussed in appendix A, we shall now focus on the design of our survey and how we have aimed to address the mentioned issues.

Methodology of assessing impact

In order to assess the impact of non-cognitive learning on cognitive learning outcomes, we have used an ordinary least square regression technique considering the overall index for non-cognitive skills as an independent variable and cognitive learning outcomes measured on a test performed for the students of elementary education on their mathematics competency. In addition to the non-cognitive skills, the learning outcomes of the children may depend on many other socio-economic and school related variables, and these variables are also controlled within the regression equation. Moreover, all the sub-indices of the non-cognitive skills have also been considered as independent variables in another set of regression equations to assess their individual impact on the cognitive learning outcomes. For all the regression models, the robustness of the significance and sign of the impact of the non-cognitive skills have been checked by the inclusion of other variables. A detailed description of the independent variables is given in table 2A in the appendix.

Estimated Results

Cognitive learning outcomes

Table 2: Descriptive Statistics of Learning Outcomes

Variable	No. of observations	Mean	Standard Deviation	Minimum	Maximum
Mathematics learning outcomes	256	13.49	3.84	2	21

Source: Authors' estimation.

Table 2 presents the descriptive statistics of results that were observed from the Mathematics tests that were administered to students. This test was designed based on the curriculum being taught to the students by the school and tried to analyse their conceptual understanding. Bearing that in mind, we observe test scores that have a low mean with a high degree of variance. The students managed to achieve an average score 13.49 out of 21. There is a wide variation in the scores across students, which have been captured based on different measures of inequality and are presented in table 3.

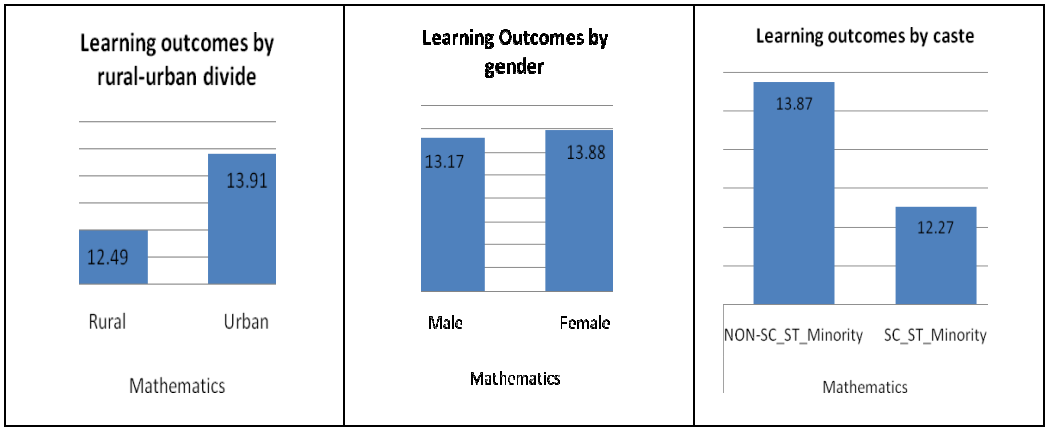
Table 3: Inequality in the Scores across Students for Mathematics Test

Measures of Inequality	Mathematics test
Coefficient of variation	0.28
Gini coefficient	0.16
Mehran measure	0.25
Piesch measure	0.11
Kakwani measure	0.03
Theil entropy measure	0.05
Theil mean log deviation measure	0.06
Atkinson Measure	0.05

Source: Authors' estimation.

There is a substantial amount of inequality existing across the students' Mathematics learning outcomes and it does differ based on different measures of inequality. In addition to the inequality across students, group-based inequality by gender, caste and rural-urban divide may also persist in the learning outcomes. Therefore, differences in learning outcomes by rural-urban divide, gender and caste have been presented in figure 1.

Figure 1: Differences in Learning Outcomes by Rural-Urban Divide, Gender and Caste

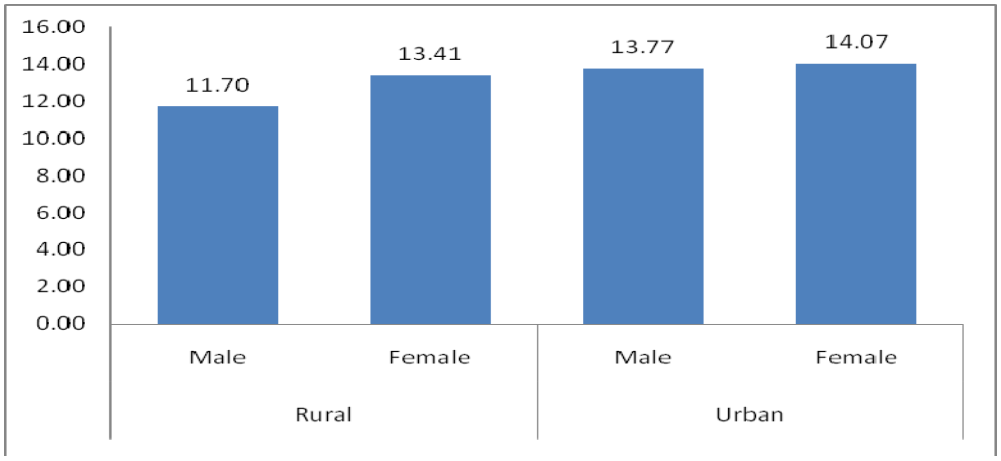


Source: Authors' estimation.

Figure 1 shows that the students belonging to urban regions have shown better performance in terms of average Mathematics learning outcomes compared to the students from rural regions. Moreover, the performance of the students belonging to disadvantaged social groups (Scheduled Castes (SC) and Scheduled Tribes (ST) and Minorities) is lower than those belonging to the General category. These results reflect what has been seen in the major surveys of learning outcomes undertaken in India (like the Annual School of Education Reports or the National Achievement Survey). However, an interesting aberration is noticed when it comes to the performances of female students, who have performed better than their male counterparts. More interestingly, female students' performance is better compared to male students within both rural and urban areas (figure 2) and also within different social groups (i.e., within both (a) SC, ST and Minorities and (b) non-SC, non-ST and non-Minorities)

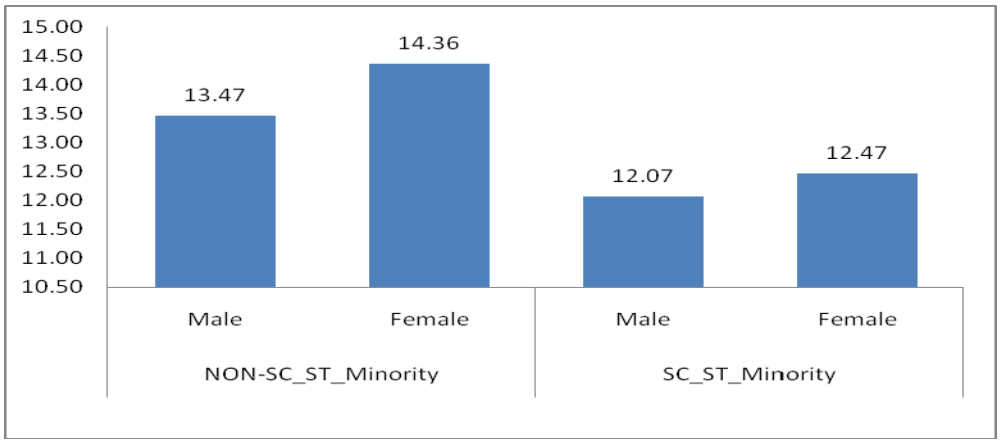
(figure 3). It is also important to note that the difference in learning outcomes between the male and female students has been found to be higher in the rural region compared to the urban (figure 2).

Figure 2: Differences in Learning Outcomes between Male and Female within Rural and Urban Areas



Source: Authors' estimation.

Figure 3: Differences in Learning Outcomes between Male and Female within Different Social Groups



Source: Authors' estimation.

The above figures illustrate the gender gap in the learning outcomes descriptively. However, it is important to see whether the gap is statistically significant or not. In order to test the statistical significance of the gender gap in the learning outcomes, we have performed t-test of mean difference of the learning outcomes between different groups by gender, castes and rural-urban divide. The t-test results have been reported in table 4.

Table 4: t-test of Mean Differences of the Learning Outcomes between Different Groups.

	Group-1			Group-2			95% CI for Mean Difference	t-value	Degrees of freedom
	Mean	Std. Err.	No. of observa-tions	Mean	Std. Err.	No. of observa-tions			
Between Male (group-1) and Female (group-2)	13.17	0.34	138	13.88	0.33	118	(-1.66, 0.23)	-1.49	254
Between Rural (group-1) and Urban (group-2)	12.49	0.48	74	13.91	0.27	182	(-2.45, -0.39)	-2.71***	254
Between Non-SC_ST_Minority (group-1) and SC_ST_Minority (group-2)	13.87	0.25	196	12.27	0.60	60	(0.50, 2.71)	2.87***	254

Note: ***, ** indicate 1 per cent and 5 per cent level of statistical significance, respectively.

Source: Authors' estimation.

Table-4 shows that test scores differences (a) between the urban and rural populations and (b) between the social groups are found statistically significant. Further, no statistically significant difference in learning outcomes between males and females has been found.

Learning outcomes and Non-Cognitive Skills

We have already discussed in the methodology section that we have first constructed eight sub-indices for non-cognitive skills based on eight broad parameters viz. Consistency, Perseverance of effort, Growth mindset, Conscientiousness, Academic behaviour, Self-regulated learning, Self-control and School climate using the polychoric PCA technique. Subsequently, using those eight sub-indices of non-cognitive skills, we have constructed an overall index for non-cognitive skills. Table 5 features our results of the correlations that exist between Mathematics test scores and indices of non-cognitive skills.

Table 5: Correlation Coefficients of Mathematics Learning Outcomes and Non-Cognitive Skills

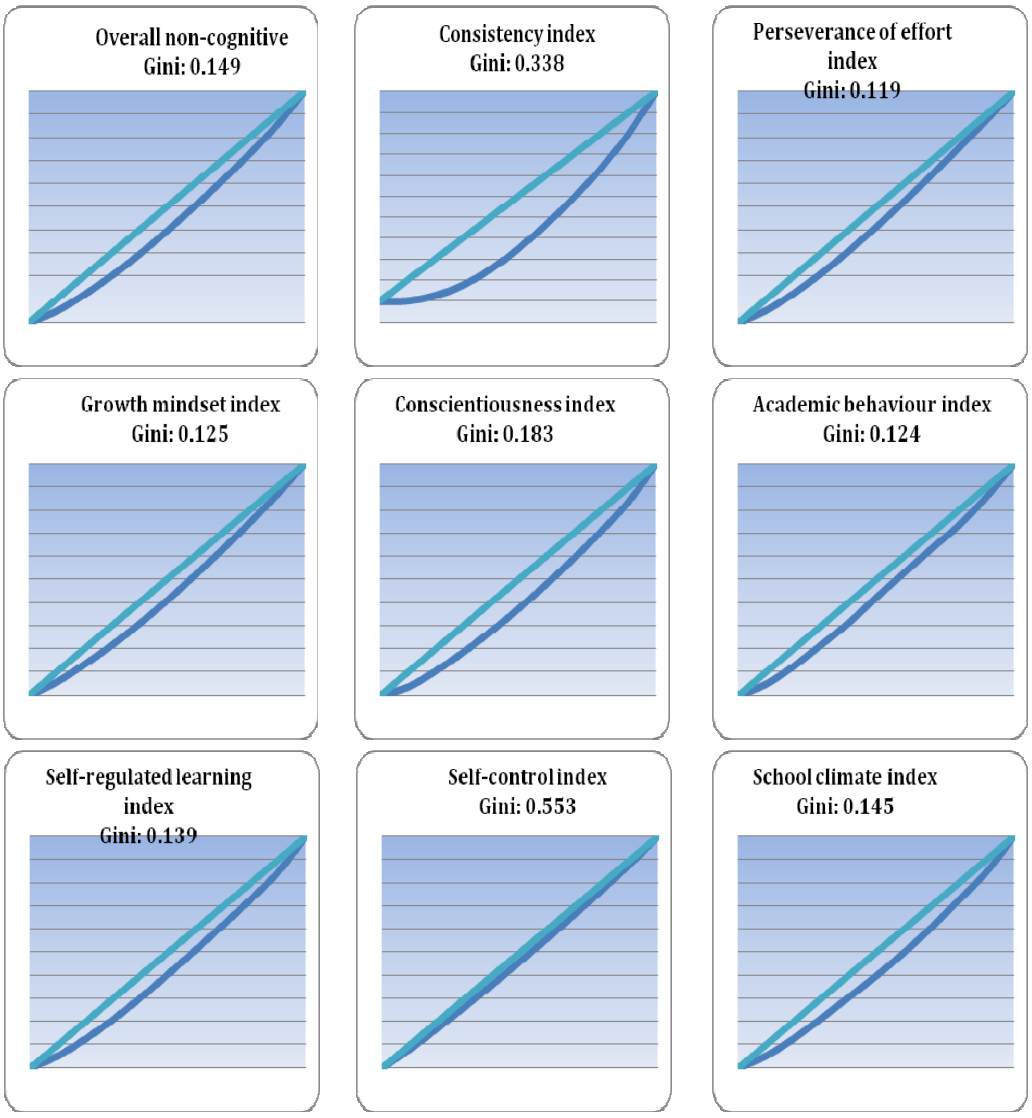
	Mathematics scores
Consistency index	-0.11**
Perseverance of effort index	0.24***
Growth mindset index	0.29***
Conscientiousness index	0.20***
Academic behaviour index	0.10**
Self-regulated learning index	0.06
Self-control index	-0.02
School climate index	0.22***
Overall index for non-cognitive skills	0.26***

Note: ***, ** indicate 1 per cent and 5 per cent level of statistical significance, respectively.

Source: Authors' estimation.

The table 5 confirms highly significant correlations between 5 out of the 7 non-cognitive skills and the test scores in Mathematics. Measures like Perseverance of effort or "Grit", Growth Mindset and Conscientiousness have been found to be positively correlated to the Mathematics test scores, with 1 percent level of significance while academic behaviour is also strongly correlated with a positive relationship (5 per cent level of significance). The strong positive correlations of Perseverance of effort and Conscientiousness is understandable, given the measures are similar in nature. The index on school climate created to capture the overall environment in a school has also been found to have a strong positive co-relationship with the Mathematics test scores. Overall, the combined index for non-cognitive skills has been found to have strong positive correlations with Mathematics test scores.

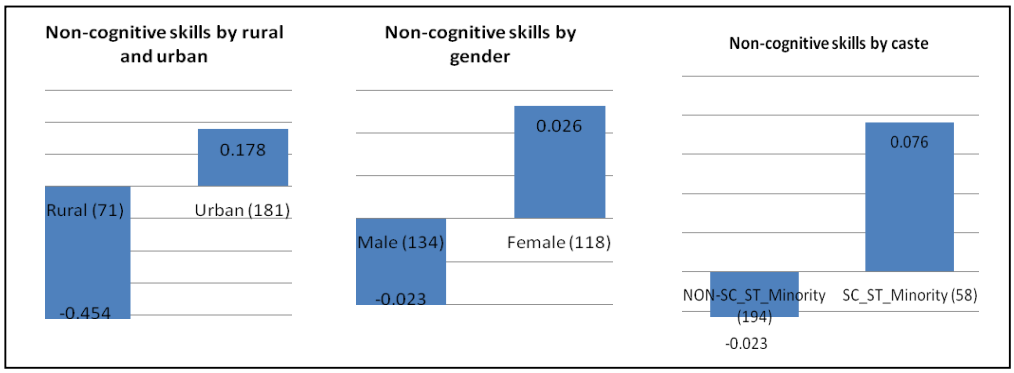
Figure 5: Lorenz Curve of the Overall Index and Sub-indices of Non-Cognitive Skills across Students



Source: Authors' estimation.

When the inequality of the non-cognitive skills are studied by its different indicators (Figure 5), Conscientiousness and Consistency indices have been found with high levels of inequality (with Gini coefficients 0.338 and 0.183 respectively) compared to the other indicators of non-cognitive skills. Self-control has the lowest inequality among all the measures (Gini coefficient 0.053) while the Gini coefficient for the overall non-cognitive index stands at 0.149.

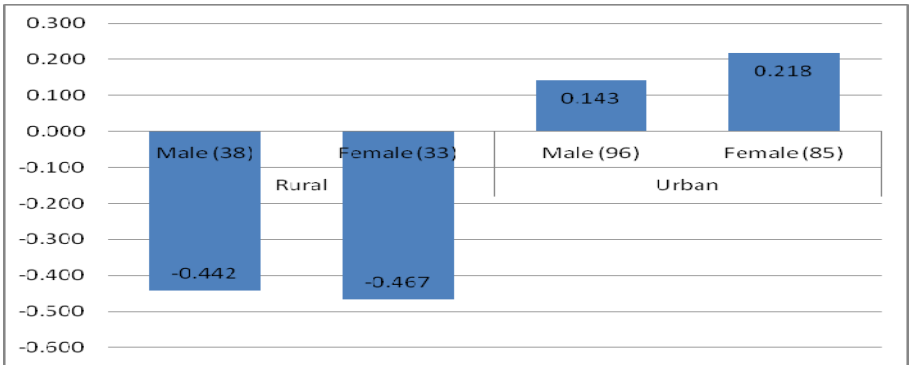
Figure 6: Differences in Overall Non-Cognitive Skills by Rural-Urban Divide, Gender and Caste



Source: Authors' estimation.

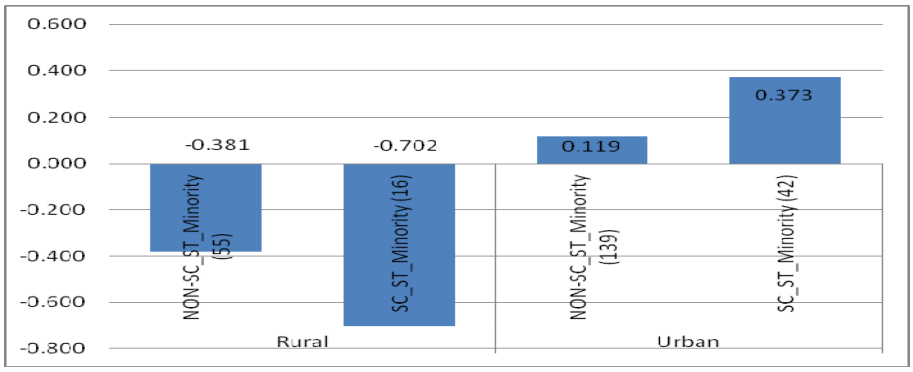
Figure 6 confirms that there is a large difference in terms of the overall non-cognitive skills possessed by students from the urban and rural backgrounds. Students from urban backgrounds have a far higher score in non-cognitive skills than students from rural backgrounds. When assessed from a gender perspective, female students considerably outperform male students here as well while students from socially backward groups have been seen to have lower scores than the students from General category. However, when we have assessed the overall non-cognitive skills difference between males and females within rural and urban areas, it is seen that females possess lower non-cognitive skills compared to males in rural areas, whereas they accounts for higher non-cognitive skills in urban areas (figure 7).

Figure 7: Differences in Overall Non-Cognitive Skills between Males and Females within Rural and Urban Areas



Source: Authors' estimation.

Figure 8: Differences in Overall Non-Cognitive Skills between Males and Females within Different Castes



Source: Authors' estimation.

However, when the performances of the social groups are categorised based on the urban-rural setting, students from SC/ST backgrounds are found to fare better than students in the General category in the urban regions (Fig 8). We believe this is a result of a change of setting sociologically, leading to greater equity in opportunities provided to students from the SC/ST category in urban settings.

Impact of non-cognitive learning on cognitive learning

While our findings have shown strong correlations between non-cognitive skills and test scores of students, causal relationships are yet to be identified. Table 6 confirms that the overall index for non-cognitive skills has a significant causal relationship with the test scores achieved in Mathematics. In fact, the positive and significant impact of overall non-cognitive skills on Mathematics learning is found robust as the results are seen consistent with the sign and statistical significance of the coefficient of the overall non-cognitive skills with the inclusion of more variables under different specifications.

Moreover, negative and significant coefficients for SC, ST and Minority students indicate that they account for lower scores compared to General caste students both in terms of Mathematics tests. Age of the school has positive and significant impact on Mathematics learning outcomes. Surprisingly, students studying in government schools account for higher impact on Mathematics learning outcomes compared to private schools in our analysis, which portrays a sharp contradictory picture of the existing studies. Further, students studying in schools with a pupil-teacher ratio that lies between 15 and 24 have a positive impact on Mathematics learning outcomes.

Table 6: Impact of Overall Index for Non-Cognitive Skills on Mathematics and English Learning Outcomes

Variables	Mathematics learning		
	Specification-1	**Specification-2**	**Specification-3**
Overall index for non-cognitive skills	0.63*** (0.16)	0.38** (0.19)	0.41** (0.19)
Female Ref: Male	0.68 (0.45)		0.62 (0.45)
SC/ST/Minority Ref: Non-SC,ST & Minority	-1.58** (0.62)		-2.16*** (0.53)
Father's education above SSLC Ref: Father's education SSLC and lower			-0.81 (0.79)
Mother's education above SSLC Ref: Mother's education SSLC and lower			1.08 (1.19)
Attended pre-school Ref: Didn't attend			0.13 (0.82)
Received help at Home Ref: Didn't receive			-0.3 (0.57)
Watch television Ref: Don't watch			-0.07 (1.08)
Age of the school		0.02** (0.01)	0.02*** (0.01)
Urban Ref: Rural		0.06 (0.63)	0.18 (0.66)
Government school Ref: Private school		1.48** (0.69)	1.26* (0.73)
No. of times CRC visited in the school		-0.12 (0.07)	-0.11 (0.08)
No. of times BRC visited in the school		0.18 (0.09)	0.15 (0.11)
PTR less than 15 Ref: PTR more than 25		0.71 (1.12)	1.9 (1.17)
PTR between 15 and 24 Ref: PTR more than 25		1.81*** (0.69)	2.38*** (0.67)
Student classroom ratio (SCR)		0.05 (0.04)	0.08** (0.04)
SCR-square		0 (0)	-0.0003 (0)
Constant	13.63*** (0.34)	9.93*** (1.27)	9.49*** (2.06)
No. of observations	251	246	246
F	8.21	10.52	8.54
Probability >F	0	0	0
R-squared	0.104	0.247	0.303
Root MSE	3.602	3.336	3.259

Note: ***, ** indicate 1 per cent and 5 per cent level of statistical significance, respectively.
Source: Authors' estimation.

Out of the specific non-cognitive skills, three out of the seven sub-indices (Perseverance, Growth mindset and Conscientiousness) were found to have strong causal relationships with the Mathematics test scores (table 7). Moreover, Consistency in sign and statistical significance of the coefficients associated with the aforementioned sub-indices across three specifications with different number of variables show the robustness in the relationship. Perseverance of effort has also been found to have a strong positive relationship with the English test scores. Further, in table 7 also, the coefficients for SC, ST and Minority students have been found negative and significant, which indicate that SC, ST and Minority students account for lower scores compared to General caste students both in terms of Mathematics and English tests. However, positive and significant coefficients for the variable female in table 7 depict that females account for higher score in Mathematics test compared to males. Like table 6, students studying in government schools account for higher impact on Mathematics

learning outcomes compared to private schools. Further, students studying in schools with a pupil-teacher ratio lies between 15 and 24 have a positive impact on Mathematics learning outcomes.

Table 7: Impact of Different Sub-indices of Non-Cognitive Skills on Mathematics and English Learning Outcomes

Variables	Mathematics learning		
	Specification-1	Specification-2	Specification-3
Consistency index	0.12 (0.19)	0.16 (0.17)	0.09 (0.18)
Perseverance of effort index	0.61** (0.3)	0.55* (0.3)	0.5* (0.3)
Growth mindset index	0.91*** (0.24)	0.5** (0.24)	0.57** (0.23)
Conscientiousness index	0.86** (0.44)	0.9** (0.46)	0.98** (0.48)
Academic behaviour index	-0.23 (0.37)	-0.23 (0.36)	-0.29 (0.35)
Self regulated learning index	-0.23 (0.35)	-0.24 (0.35)	-0.22 (0.36)
Self control index	0.01 (0.2)	0.15 (0.2)	0.06 (0.19)
School climate index	0.49 (0.37)	0.33 (0.4)	0.27 (0.42)
Female Ref: Male	0.9** (0.44)		0.78* (0.42)
SC/ST/Minority Ref: Non-SC, ST & Minority	-1.65*** (0.57)		-2.19*** (0.51)
Father's education above SSLC Ref: Father's education SSLC and lower			-0.64 (0.76)
Mother's education above SSLC Ref: Mother's education SSLC and lower			1.35 (1.27)
Attended pre-school Ref: Didn't attend			-0.08 (0.78)
Received help at Home Ref: Didn't receive			-0.26 (0.53)
Watch television Ref: Don't watch			0.07 (1.05)
Age of the school		0.02*** (0.01)	0.03*** (0.01)
Urban Ref: Rural		-0.12 (0.63)	-0.06 (0.66)
Government school Ref: Private school		1.29* (0.68)	1.05 (0.72)
No. of times CRC visited in the school		-0.17** (0.08)	-0.15* (0.08)
No. of times BRC visited in the school		0.16 (0.1)	0.12 (0.11)
PTR less than 15 Ref: PTR more than 25		0.57 (1.09)	1.69 (1.14)
PTR between 15 and 24 Ref: PTR more than 25		1.55** (0.69)	2.08*** (0.65)
Student classroom ratio (SCR)		0.05 (0.04)	0.08** (0.04)
SCR-square		0 (0)	0 (0)
Constant	9.12*** (2.01)	7.49*** (2.27)	7.31** (2.98)
No. of observations F Probability >F R-squared Root MSE	251 5.87 0 0.20 3.453	246 6.63 0 0.30 3.266	246 6.56 0 0.359 3.174

Note: ***, ** indicate 1 per cent and 5 per cent level of statistical significance, respectively.
Source: Authors' estimation.

Conclusion

This study examines the impact of non-cognitive factors on students' cognitive learning outcome based on a primary survey conducted across 256 students in 40 schools in Karnataka.

Based on the analysis of learning outcomes of Mathematics, a low mean with a high degree of inequality have been observed. The overall non-cognitive index was found to be a responsible factor for the gloomy picture of Mathematics learning outcomes. While checking for robustness and causal relationships, the overall non-cognitive index was found to have a positive and significant causal relationship with the Mathematics test scores across different specifications of the regression equation. Moreover, five indicators of non-cognitive skills have been found to have significant positive correlation with the Mathematics test scores. These include Perseverance of Effort or "Grit", Growth Mindset, Conscientiousness, Academic Behaviour and Consistency. Out of the sub-indices of non-cognitive skills, three out of the seven sub-indices (Perseverance, Growth mindset and Conscientiousness) were found to have strong causal relationships with the Mathematics test-scores. Moreover, consistency in sign and statistical significance of the coefficients associated with the aforementioned sub-indices across three specifications with different number of variables show the robustness in the relationship. Hence, policies should focus on promoting non-cognitive skills among children that shape their cognitive learning outcomes.

References

Barsalou, L W (2010). Grounded Cognition: Past, present, and future. *Topics in Cognitive Science*, 2 (4): 716-24.

Bethell, George and Jayshree Oza (2006). *Assessing Learning Outcomes: Policies Progress and Challenges.* (Accessed on October 27 2017) (http://rmsaindia.gov.in/administrator/components/com_pdf/pdf/cf76ea85f9799e7b5654bf8b06a0282d-SSA-Learning-Assessment-Research-Study-Report--13-06.pdf)

Blackwell, L S, K H Trzesniewski and C S Dweck (2007). Implicit Theories of Intelligence Predict Achievement across an Adolescent Transition: A Longitudinal Study and an Intervention. *Child Development*, 78: 246-63.

Duckworth, A (2016). *Grit: The power of passion and perseverance*. New York, NY: Simon & Schuster.

Duckworth, A L and P D Quinn (2009). Development and Validation of the Short Grit Scale (Grit-S). *Journal of Personality Assessment*, 91: 166-74.

Duckworth, A L and D S Yeager (2015). Measurement Matters: Assessing Personal Qualities other than Cognitive Ability for Educational Purposes. *Educational Researcher,* 44: 236-51. doi:10.3102/0013189X15584327

Duckworth, A L, C Peterson, M D Matthews and D R Kelly (2007). Grit: Perseverance and Passion for Long-term Goals. *Journal of Personality and Social Psychology*, 92 (6): 1087.

Duckworth, A L and M E P Seligman (2005). Self-discipline outdoes IQ in predicting academic performance of adolescents. *Psychological Science*, 16: 939-44.

Educational Trust, Pratham (2016). *Annual State of Education Report (Rural) 2016.* New Delhi: ASER Centre. (Accessed on October 27 2017) (http://img.asercentre.org/docs/Publications/ASER%20Reports/ASER%202016/aser_2016.pdf)

———— (2016). Annual Status of Education Report (ASER) and National Achievement Surveys (NAS): A Comparison. (Accessed on October 27, 2017) (http://img.asercentre.org/docs/Publications/ASER%20Reports/ASER%202014/aserandnas-acomparison.pdf)

Farrington, C A, M Roderick, E Allensworth, J Nagaoka, T S Keyes, D W Johnson and N O Beechum (2012). *Teaching Adolescents to become Learners: The Role of Non-cognitive Factors in Shaping School Performance: A Critical Literature Review*. Chicago: University of Chicago Consortium on Chicago School Research.

Glewwe, P, Q Huang and A Park (2017). Cognitive Skills, Non-cognitive Skills, and School-to-Work Transitions in Rural China. *Journal of Economic Behavior & Organization*, 134: 141-64.

Gutman, L M and I Schoon (2013). *The Impact of Non-cognitive Skills on Outcomes for Young People: Literature Review*. London: University of London, Institute of Education.

John, O P and S Srivastava (1999). The Big Five Trait Taxonomy: History, Measurement, and Theoretical Perspectives. In L A Pervin and O P John (eds), *Handbook of Personality: Theory and Research* (2nd ed). New York, NY: Guilford Press. Pp 102-38.

Krishnan, Pramila and Sofya Krutikova (2013). Non-cognitive Skill Formation in Poor Neighbourhoods of Urban India. *CEPR Discussion Paper No. DP9540*. Available at SSRN: https://ssrn.com/abstract=2291341

Mehta, Prayag (1969). The Achievement Motive in High School Boys. National Council of Educational Research and Training. (https://catalogue.nla.gov.au/Record/2613929)

OECD (2012). Ready to Learn – Students' Engagement, Drive and Self-beliefs. (https://www.oecd.org/pisa/keyfindings/pisa-2012-results-volume-III.pdf) (Accessed on September 19, 2018)

Pintrich, P R and E De Groot (1990). Motivational and Self-regulated Learning Components of Classroom Academic Performance. *Journal of Educational Psychology*, 82: 33-40.

Rosen, J A, E J Glennie, B W Dalton, J M Lennon and R N Bozick (2010). *Non-cognitive Skills in the Classroom: New Perspectives on Educational Research*. Research Triangle Institute.

Tangney, J P, R F Baumeister and A L Boone (2004). High Self-control Predicts Good Adjustment, Less Pathology, Better Grades, and Interpersonal Success. *Journal of Personality,* 72: 271-322.

Tsukayama, E, A L Duckworth and B Kim (2013). Domain-specific Impulsivity in School-age Children. *Developmental Science*, 16: 879-93.

West, M, M A Kraft, A S Finn, R Martin, A L Duckworth, C F O Gabrieli and J D E Gabrieli (2016). Promise and Paradox: Measuring Students' Non-cognitive Skills and the Impact of Schooling. *Educational Evaluation and Policy Analysis*, 38 (1): 148-70. doi:10.3102/0162373715597298

Zimmerman, B J and M Martinez-Pons (1986). Development of a Structured Interview for Assessing Student Use of Self-regulated Learning Strategies. *American Educational Research Journal,* 23: 614-28.

Appendix-A

Concepts that were tested in Mathematics

NAS	Educational Initiative
Operations	Number Sense
Geometry	Four Basic Arithmetic Operations
Measurement	Fractions
Number System	Geometry
	Measurement
	Problem Solving

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