Can We Improve Learning Outcomes of Schoolchildren from the Poorest Families by Investing into Their Non-Cognitive Skills? Causal Analysis Using Propensity Score Matching

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The article was submitted to the Editorial Board in December 2021

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Abstract

The research aims to discover how non-cognitive skills influence students` academic achievement. Particular emphasis was put on how non-cognitive skills influence academic achievement in students from families with low socio-economic status. The study uses the data of the Programme for International Student Assessment (PISA) collected in Russia in 2018. The PISA-2018 provides nationally representative data that contains information from more than 7,000 students in the 9th grade in Russia. For data analysis, propensity score matching was used as one of the causal analysis methods used in econometrics. The study results reveal that the development of such non-cognitive skills as growth mindset, self-efficacy, and grit lowers students' probability to become low achievers. The effect is particularly strong for the students from the poorest families. In conclusion, the authors suggest recommendations for educational policy on the inclusion of socio-emotional learning programs in educational standards of school education.

Keywords

non-cognitive skills, socio-economic status, human capital, academic achievements, propensity score matching, growth mindset, grit, self-efficacy.

For citing Avanesian G.A., Borovskaya M.A., Ryzhova V.S., Kirik V.A., Egorova V.A., Bermous A.G. (2022) Mozhno li uluchshit' uspevaemost' shkol'nikov iz bedneyshikh semey, investiruya v ikh nekognitivnye navyki? Kauzal'ny analiz metodom sopostavleniya mer sklonnosti [Can We Improve Learning Outcomes of Schoolchildren from the Poorest Families by Investing into Their Non-Cognitive Skills? Causal Analysis Using Propensity Score Matching]. Voprosy obrazovaniya / Educational Studies Moscow, no 1, pp. 13–53. https://doi.org/10.17323/1814-9545-2022-1-13-53

Quality education is one of the development priorities for the international community. The Sustainable Development Goals adopted by the United Nations General Assembly in 2015 and lie at the core of the 2030 Agenda for the development of world economies, prioritize, among other things, "ensuring inclusive and equitable quality education and promoting lifelong learning opportunities for all" (Sustainable Development Goal 4). One of the prerequisites for achieving this goal is educational equity when vulnerable and socio-economically deprived groups have the same opportunities as more advantaged groups to access quality education. In other words, belonging to a vulnerable group should not be a factor that constrains a child in the accumulation of human capital. Sustainable Development Goal Indicator 4.1.1 (c) measures the proportion of children achieving a minimum proficiency level in reading and mathematics at the end of lower secondary education. In Russia, it was 78% in both reading and mathematics in 2018, which was a significant decline compared to 2015, when the indicator had reached 84% and 81%, respectively[1]. It is likely that without targeted public policy measures the proportion of schoolchildren who do not achieve the minimum proficiency level can hardly be reduced to zero by 2030.

Hence, without targeted policy interventions, the country could face a significant deficit of human capital needed for sustainable socio-economic development, and urgent measures need to be taken today to improve the skills of young Russians. Prospective government efforts to address inequity in education gain particular relevance in this context . Evidence from international comparative studies confirms that socio-economic status of a child's family appears to be a notable factor of low academic achievement [OECD, 2016a]. For example, in Russia, it explains about 7% of the variation in the learning outcomes of schoolchildren in lower secondary school. In addition, low achievers in reading often also underachieve in mathematics, which points to a high probability of overlap between the two statistical distributions [OECD, 2016b].

Socio-economic status is consistently associated with cognitive skills [Farah, 2017] and influences child's cognitive abilities through-

[1] UNESCO (2021) Sustainable Development Goals: 4.1.1 Achieving at Least a Minimum Proficiency Level in Mathematics at the End of Primary: http://data.uis.unesco.org/index.aspx?queryid=3692

out all stages of learning. Evidence from behavioral neuroscience confirmed the long-term nature of this relationship: the difference in IQ between children from the wealthiest and poorest classes at age two, which is only 2, increases over the course of life, reaching 15 at the age of sixteen years old [Stumm von, Plomin, 2015].

Thus, education systems that do not adopt targeted measures to compensate for the socio-economic disadvantage of schoolchildren inevitably reproduce inequality in human capital accumulation, thereby blocking channels of upward social mobility. Inequality in learning outcomes can also be caused by factors other than socio-economic ones, such as pedagogy, school climate, and parental involvement. However, sustained, equity-focused improvement in educational outcomes begins “at the tail end” — with targeted support for those with the lowest educational outcomes [Crouch, Rolleston, 2017; Crouch, Rolleston, Gustafsson, 2021; Akmal, Pritchett, 2021].

In other words, reducing the proportion of schoolchildren who fail to meet a minimum proficiency level in reading and mathematics will not only ensure progress toward the achievement of Sustainable Development Goal Indicator 4.1.1 (c) but will also eliminate inequality in the key skills gained through the lower secondary education. Closing the opportunity gap that results from differences in family status should become a priority in education policy. This will not only ensure equitable opportunities for human capital accumulation in general school education but will also lay the groundwork for overcoming persistent poverty: the experience of some countries confirms that high academic achievement among 15-year-old schoolchildren from the poorest families is a strong predictor of upward mobility [OECD, 2018].

In seeking ways to reduce the prevalence of low academic achievement, contemporary researchers in economics, psychology and sociology are examining non-cognitive skills as a driver of academic achievement. Non-cognitive skills are defined as patterns of thought, feelings and behavior of individuals that may continue to develop throughout their lives and that play an important role in the educational process [Garcia, 2016]. In other words, in addition to academic knowledge, learners should develop behavioral strategies, skills, and attitudes necessary for academic success that are not captured by cognitive test scores [Farrington et al., 2012]. In the scientific literature, non-cognitive skills are also known as socio-emotional skills [Attanasio et al., 2020; Zhou, 2017], 21st-century skills[2], trans-

[2] UNESCO, UNPFA, UNICEF, UN (2015) Education 2030. Incheon Declaration and Framework for Action for the Implementation of Sustainable Development Goal 4. Towards Inclusive and Equitable Quality Education and Lifelong Learning for All: http://uis.unesco.org/sites/default/files/documents/education-2030-incheon-framework-for-action-implementation-of-sdg4-2016-en_2.pdf

versal skills [Cinque, Carretero, Napierala, 2021], or soft skills [Koch, Nafziger, Nielsen, 2015; Laker, Powell, 2011].

In this paper we seek to answer the following research question: to what extent can non-cognitive skills improve the educational outcomes of schoolchildren, especially those from families with low socio-economic status? To put it differently, how strong is the causal effect of non-cognitive skills on academic achievement, and does the strength of this effect change in interaction with the socio-economic status of the child's family?

The results of Russian schoolchildren in the Program for International Student Assessment (PISA) in 2018 were adopted as the data of the study. The data were analyzed by propensity score matching, a method used in econometrics for causal evaluation of the effects of public policy [Caliendo, Kopeining, 2008; Essama-Nssah, 2006; Heinrich, Maffioli, Vazquez, 2010; Basu, Meghani, Siddiqi, 2017]. The research on the influence of non-cognitive skills on learners' academic competencies as applied to Russia potentially contributes to incrementing scientific knowledge about the effect of socio-economic status on learning outcomes. The insights suggested in this paper can serve as a basis for the development of public policy measures aimed at closing the gap in human capital accumulation between schoolchildren from different socio-economic status groups by investing in their non-cognitive skills.

Review of Research on the Role of Non-Cognitive Skills in Learning

The importance of non-cognitive skills for human capital accumulation is reflected in both international and Russian educational development agenda. Indicators 4.1, 4.4, and 4.7, which measure the achievement of Sustainable Development Goal 4, describe the non-cognitive, social and emotional development of learners. According to the Incheon Declaration *Education 2030*, adopted at the World Education Forum in 2015 as a guide to achieving the SDGs in education, the education content and learning process should be focused on the development of non-cognitive skills in learners in addition to cognitive ones. The Federal State Educational Standard of Basic General Education, approved by the Ministry of Education and Science of the Russian Federation, enshrines the need to develop students' emotional intelligence, communication skills, self-control and many other non-cognitive characteristics.

A positive correlation has been empirically established between the level of non-cognitive skills and academic performance [Wanzer, Postlewaite, Zargarpour, 2019; Destin et al., 2019; Komarraju, Nadler, 2013]. Researchers particularly focus on assessing whether the negative effect of socio-economic status on academic performance can be compensated by improving the non-cognitive skills of learners from families with low socio-economic status [OECD, 2019; Claro, Paunesku, and Dweck, 2016; OECD, 2021a].

Despite the extensive research on non-cognitive skills in recent years, there is still no consensus among scholars regarding their taxonomy. Several authors [Kankaraš, Suarez-Alvarez, 2019; Lipnevich, MacCann, Roberts, 2013; OECD, 2017; Humphries, Kosse, 2017] consider the Big Five personality traits — openness to experience, conscientiousness, extraversion, agreeableness, and emotional stability (neuroticism) — as non-cognitive skills. This taxonomy is the most common, but not the only one [Danner, Lechner, Spengler, 2021]. Studies that focus on non-cognitive characteristics such as growth mindset, self-efficacy, grit/perseverance [Duckworth, 2016], self-control [Schmidt et al., 2020], achievement motivation [Steinmayr et al., 2019], and sense of belonging at school [Urvashi and Singh, 2017; Lee, 2020] also showed plausible results. Some of these skills have been tested in PISA in different years. For its Study on Social and Emotional Skills (SSES), the OECD has developed a new taxonomy that resulted from attempts to adapt the Big Five to the context of human capital accumulation in the school education system. The taxonomy includes 15 skills that make up a five-factor model and are measured in 10- and 15-year-old schoolchildren.

Previous research has identified several stable non-cognitive skills that influence academic performance, particularly among schoolchildren from low-status groups. Development of a growth mindset, a trait defined as an individual's belief in ability to develop their own capacities and intelligence, refers to one of particular factors that increase academic performance [OECD, 2019; Costa, Faria, 2018; Blackwell et. al., 2007]. As shown in a large-scale nationally representative study, schoolchildren from low-status groups are less likely than their more advantaged peers to develop a growth mindset, but targeted interventions to build this skill in low-achieving learners from poor families have a consistently positive effect on their learning outcomes [Claro, Paunesku, and Dweck, 2016; OECD, 2021a]. Thus, a growth mindset may be one of the mechanisms by which economic vulnerability affects academic performance.

The sense of belonging at school refers to the degree to which a student feels included in the social environment of the school [Goodenow, 1993] and has a need to build and maintain trust-based interpersonal relationships. The sense of belonging is consistently correlated with higher academic achievement [OECD, 2019; OECD, 2017; Abdollahi, Noltemeyer, 2018]. In particular, it has been found that the sense of belonging at school has a positive effect on the average academic performance of students from poor racial and ethnic minority families [Shook, Clay, 2012].

Self-efficacy, defined as an individual's belief in their ability to solve complex problems and cope with life's challenges [Bandura, 1997], is considered as another predictor of academic performance [Hwang et al., 2016; Köseoglu, 2015], A 1-point increase in self-efficacy leads to a 6-point increase in the average reading score of schoolchildren [OECD, 2019]. A comparative economic study of child poverty in four developing countries has found that self-efficacy, educational motivation and households' living conditions are significantly associated with each other [Dercon, Krishnan, 2009]. Deficit of self-efficacy in children from poor families consistently correlates with low self-efficacy in their parents, suggesting the intergenerational transmission of psychosocial characteristics of those living in poverty [Krishnan, Krutikova, 2013]. Children with poor self-efficacy do not strive for high educational and professional achievements [Bandura et al., 2001] and therefore fail to escape poverty [Wuepper, Sauer, 2016; Chiapa et al., 2012; Tafere, 2014; Pasquier-Doumer, Brandon, 2015].

Task mastery, or, in other words, dispositional commitment to work hard to achieve specific goals, is another skill that positively influences academic achievement in mathematics and reading [Józsa, Molnár, 2013; Broussard, Garrison, 2004; Suprayogi, Ratriana, Wulandari, 2019]. Its effect is especially visible in primary grades but, according to researchers, does not remain constant throughout schooling and tends to decrease in adolescence [Józsa, Kis, and Barrett, 2019].

Grit has a positive impact on learners' academic achievement at all levels of education [Wolters, Hussain, 2015; Lee, Sohn, 2017; Lam, Zhou, 2019]. In one experimental study, grit-enhanced interventions in the educational process increased the number of students completing courses satisfactorily by 6.4% [Paunesku et al, 2015]. The evidence regarding the impact on academic achievement of fear of failure, that is, a student's lack of confidence in themselves and their own abilities, is mixed. In countries where schoolchildren receive above-average reading scores in international surveys, the lack of self-confidence is positively related to academic achievement, while in countries with low scores on reading tests, confident students demonstrate higher academic achievement [OECD, 2019].

The level of development of both cognitive and non-cognitive skills in schoolchildren is determined by environmental factors, which are often more significant than hereditary factors (up to 60%) [Vukasović, Bratko, 2015]. Family socio-economic status is highly likely to be a confounding variable, that is, it may have an effect on both cognitive and non-cognitive skills of a child and determine the nature of the relationship between them. On the one hand, non-cognitive skills are relatively stable; on the other hand, they are flexible in childhood and adolescence, meaning that the education system could improve them through targeted social programs of human capital development [Heckman, Kautz, 2014].

Economic studies have shown that the most effective programs for non-cognitive skills development are those conducted in early childhood, in the preschool stage [Heckman, 2006; Almlund et al., 2011]. The econometric analysis confirmed that the return on investment in non-cognitive skills development is the higher the earlier the investment is made, especially when it comes to stimulating the achievements of the poor [Heckman, 2000]. Socio-emotional learning programs have succeeded in improving the academic achievement of the poorest children, and longitudinal measurements have confirmed the upward social mobility of participants in these programs [Knudsen et al., 2006]. As a consequence, the statement "skills beget skills" has become popular among scholars, cementing the relationship between cognitive and non-cognitive characteristics.

Studies on the impact of non-cognitive skills on individuals' educational and occupational outcomes conducted on a Russian sample, show, in particular, that non-cognitive components of human capital generate a stable return in the labor market, influencing both employability and labor remuneration [Гимпельсон, Зудина, Капелюшников, 2020; Рожкова, 2019; Maksimova, 2019]. The majority of economic studies have been conducted on an adult sample. At the same time, experts agree that the development of non-cognitive skills is a new challenge for the theory and practice of education in Russia [Кузьминов, Сорокин, Фрумин, 2019].

During the pilot phase of the Survey on Social and Emotional Skills launched by the Organization for Economic Cooperation and Development, it has been found that in a representative sample of 10- and 15-year-old Moscow schoolchildren inequality in key skills increases depending on family economic status, and schoolchildren from the poorest households are identified as a vulnerable group in terms of accumulation of non-cognitive components of human capital [OECD, 2021b. P. 23]. Moreover, schoolchildren with poorly developed non-cognitive skills have fewer channels for social mobility, judging by their expectations regarding higher education and choice of profession [Ibid. P. 13–16]. The findings of the OECD study correspond to the results obtained by Russian economists on a representative national sample that has confirmed the influence of non-cognitive skills on the intention to receive higher education and on the choice of the field of study [Рожкова, Рощин, 2021a; 2021b]. Increased scientific knowledge in this area could contribute to the development of recommendations for public policy aimed at creating inclusive education systems in which the accumulation of human capital in schoolchildren from the poorest families is built on the principle of equity and provides them with the skills and competencies necessary for intergenerational upward mobility.

Data and Methodology

The study adopted PISA 2018 data for Russia, which provide nationally representative sample of more than 7,000 schoolchildren at the age of 15 years old. In addition to information on academic achievement, the PISA questionnaires contain data on a number of non-cognitive characteristics of schoolchildren. This study measures such non-cognitive skills as growth mindset, sense of belonging at school, task mastery, self-efficacy, grit, and self-confidence[3]. The proposed questions have undergone cognitive and validity tests in all countries participating in the survey and have been included in the PISA questionnaires since 2009. The questions used to measure the non-cognitive skills analyzed in this study are presented in Appendix 1. In order to calculate the aggregate indices for the above non-cognitive characteristics, the OECD used item response theory regression models. For the analysis, we standardized the variables to the mean of the Russian sample. The sample parameters, as well as descriptive statistics on learning outcomes and aggregate scores for non-cognitive skills, are presented in Table 1. The breakdown of standardized scores for non-cognitive skills and learning outcomes by key groups is presented in Appendix 2.

Table 1. **Sample Parameters and Descriptive Statistics**

Gender							
Male: 3.747				Female: 3.861			
Residence							
Urban: 5.536				Rural: 1.691			
Learning outcomes							
	Min	Mean	Median	Max	*SD*	Skewness	Kurtosis
Reading	183	480	482	746	90	–0.14	–0.26
Mathematics	213	489	490	747	78	–0.11	–0.17
Non-cognitive skills							
Growth mindset	–1.88	0	0.32	1.42	1	–0.22	–0.75
Sense of belonging at school	–3.47	0	–0.06	3.86	1	1.23	4.63
Task mastery	–2.74	0	0.26	2.45	1	0.36	0.78
Self-efficacy	–3.08	0	–0.16	2.88	1	0.67	1.93
Grit	–2.15	0	–0.24	1.52	1	0.1	–0.69
Self-confidence	–2.31	0	0.05	1.97	1	–0.13	0.09

Source: authors' calculations based on the PISA 2018 data for Russia.

[3] In the PISA, fear of failure is a measure of a schoolchild's confidence in their ability to learn. To create a positive connotation, the values of this scale were transformed so that the most self-confident students, who had the lowest values on the original scale, would receive high scores.

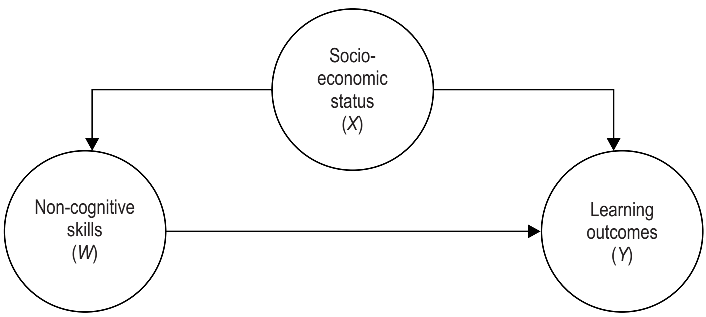
When choosing the method of data analysis, we assumed that belonging to a group with high or low academic achievement was not random and that the distribution of schoolchildren who did not achieve the minimum proficiency level in reading and mathematics was the result of several confounding factors. In other words, we selected an approach to estimating the effect of non-cognitive skills on academic performance that is not affected by the existing sample bias. Since in non-experimental cross-sectional measurements a researcher has no control over sample parameters, we used the method of propensity score matching, which estimates the causal effect of treatment in a quasi-experimental manner based on observational data . This method is often used in economics to evaluate the effectiveness of particular social programs or public policy measures, as it reduces the effect of confounding factors.

In this study, the dependent variable *Y* is binary. It indicates whether a schoolchild belongs to the group of low achievers in reading and mathematics. In PISA, low-achieving schoolchildren are those who do not reach the second level of difficulty in the relevant subject tests, which is considered to be the basic proficiency level necessary for full participation in society and competing in the labor market [OECDb, 2016. P. 37]. Schoolchildren with test results below Level 2 can answer a question on a text that requires direct inference, but are not capable of holistic logical thinking and are not able to solve more complex problems that are routinely encountered by adults in everyday life in modern economies.

The treatment variable is a non-cognitive skill W_i. Since this study focuses on six skills, six different iterations of propensity score matching are needed, each of which measures the effect of a particular non-cognitive characteristic on the probability of a student belonging to the low-achieving group. We are primarily interested in the skills that have the strongest negative effect on the likelihood of low achievement, as investing in these skills will reduce the proportion of schoolchildren who do not reach the minimum proficiency level in key competencies at the end of basic general school. By the logic of propensity score matching, six continuous variables were dichotomized to statistically discriminate students based on their levels of a particular non-cognitive skill. A borderline value of 0.5 standard deviation was applied. With this borderline value, on average about 25% of schoolchildren were assigned to the treatment group, depending on the distribution of a particular skill. Data on the size of the treatment group for each skill are presented in Appendix 3.

A measure of socio-economic status as a major confounding factor for both academic achievement and non-cognitive skills is the PISA index of economic, social, and cultural status (ESCS). This indicator is based on family information such as parental education and occupation , family wealth, and possession of cultural goods . Thus, ESCS that combines several social, economic and cultural characteristics not only reflects the state of family finances but also serves as a proxy for the comprehensive relationship between family resources and the external environment in which a child's personal development, socialization and human capital accumulation take place. ESCS is a continuous variable, an index standardized to the mean. We transformed it into an ordinal variable, the levels of which (poorest, poor, middle , rich, richest) represent equal-size twenty-percent cohorts of the sample — quintile groups. Child's gender and area of residence (urban or rural) were the control variables in the model. The relationships between the main variables used in the study are shown in Figure 1. The source code in the statistical programming language R, the source datasets, and detailed graphs and descriptions of the models presented in this article are available online on the Open Science Framework platform at the following DOI: 10.17605/OSF.IO/BYFTW

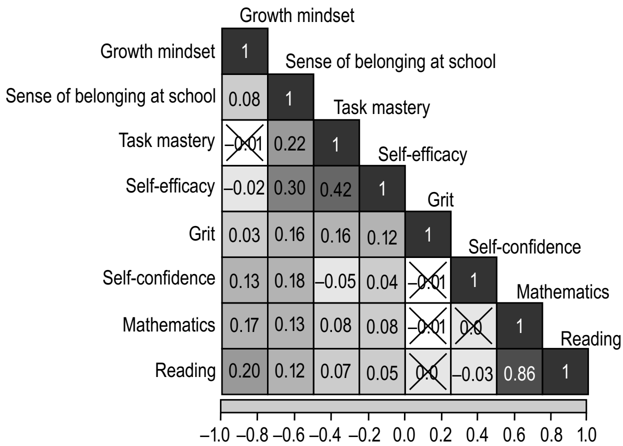
Figure 1. **Causal Model Used in the Study**



Results

The correlation analysis using Spearman's coefficient (r) revealed statistically significant correlations between a number of cognitive and non-cognitive skills. As shown in Figure 2, most correlations, while statistically significant, were nonetheless weak or moderate. This confirms that the non-cognitive characteristics analyzed represent personality traits that are different in their features. In particular, among the non-cognitive skills, the strongest positive correlation is observed between self-efficacy and the motivation to master tasks (r = .42, p < .05). Self-efficacy also moderately correlates with the sense of belonging at school (r = .30, p < .05). In turn, the sense of belonging is weakly correlated with the task mastery (r = .22, p < .05) and grit (r = .16, p < .05). Academic achievement is most strongly correlated with a growth mindset (r = .17 for mathematics and r = .20 for reading, p < .05). Of particular note in this context is the high correlation between learning outcomes in

Figure 2. **Matrix of Correlations Between Non-Cognitive and Cognitive Characteristics**

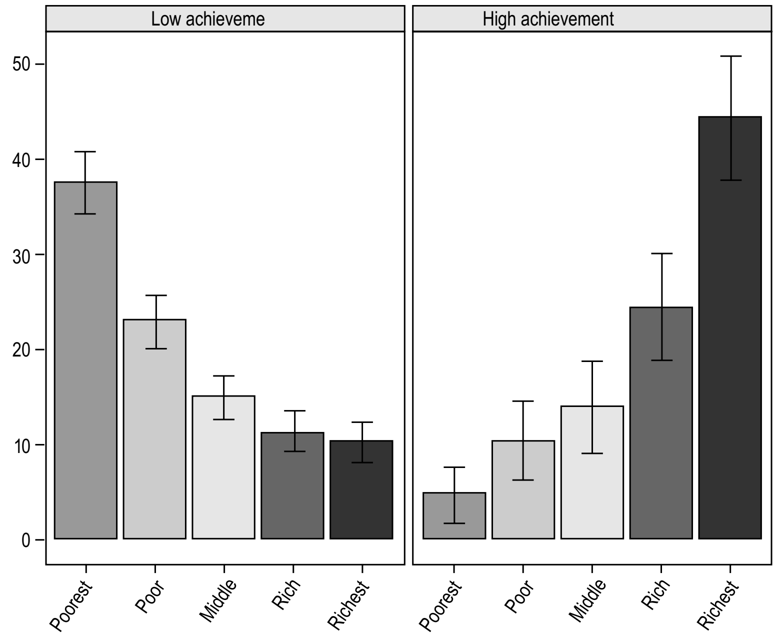


Source: authors' calculations based on the PISA 2018 data for Russia.

reading and mathematics (r = .86, p < .05). Apparently, the ability to make inferences and to logically comprehend and understand information assessed in the reading tests also lies at the core of mathematics proficiency. The high correlation between proficiency in reading and mathematics suggests that schoolchildren with low achievement in one subject area are likely to have low proficiency in the other. Our calculations based on the PISA 2018 data for Russia support this conclusion: low achievers in mathematics make up 19% of the sample, in reading — 21% of the sample, and the proportion of schoolchildren with low achievements in both domains accounts for 14%. Among low achievers in mathematics, 75% also score poorly in reading; that is, three out of four learners who do not reach the minimum proficiency level in mathematics do not reach it in reading either.

Figure 3 shows the relationship between learning outcomes and status. The higher the family's socio-economic status, the more likely the schoolchild is to demonstrate high academic achievement and vice versa. Among schoolchildren with low scores in both subject areas, 38% come from families in the lowest quintile of the PISA index of economic, social, and cultural status, and nearly half (44%) of the high achievers come from the wealthiest families in the sample, the fifth quintile. Low-achieving and high-achieving students are almost equally likely to come from the middle families (third quintile) — at approximately 15%. Among students who do not reach the minimum proficiency level in reading and mathematics skills, the lowest proportion (11%) comes from the wealthiest families; conversely, among students with outstanding academic achievement, the lowest proportion comes from the poorest families (4%).

Figure 3. **Low- and High-Achieving Students by Family Socio-Economic Status**



Source: authors' calculations based on the PISA 2018 data for Russia.

The effect of socio-economic status on cognitive and non-cognitive skills was estimated using logistic regression models. The models summarized in Table 2 test the assumption of socio-economic status as a confounding factor in the relationship between non-cognitive skills and academic achievement. In the first two models, the binary dependent variables are used to assess the association between socio-economic status and a child's belonging to the group of low (Model 1) and high (Model 2) achievers in reading and mathematics. The other four models examine the relationships between family socio-economic status and the likelihood that a particular non-cognitive characteristic is strongly present in a schoolchild.

Regression analysis shows that groups of schoolchildren from the poorest and wealthiest families have clearly unequal statistical odds of both high academic achievement and proficiency in a range of non-cognitive skills important to academic performance. This suggests the potential role of socio-economic status as a confounding factor with respect to the probability of both high academic achievement and proficiency in non-cognitive skills. For ease of interpretation, the logarithms of the odds ratios from Table 2 are converted to marginal effects and expressed in probabilities. Figure 4 shows the marginal effects of socio-economic status and other factors on the probabilities of low and high academic achievement. For example, the probability of belonging to the group that

Table 2. **Results of the Logistic Regression Models for Estimating the Impact of Family Socio-Economic Status on Children's Cognitive and Non-Cognitive Skills (Before Matching)**

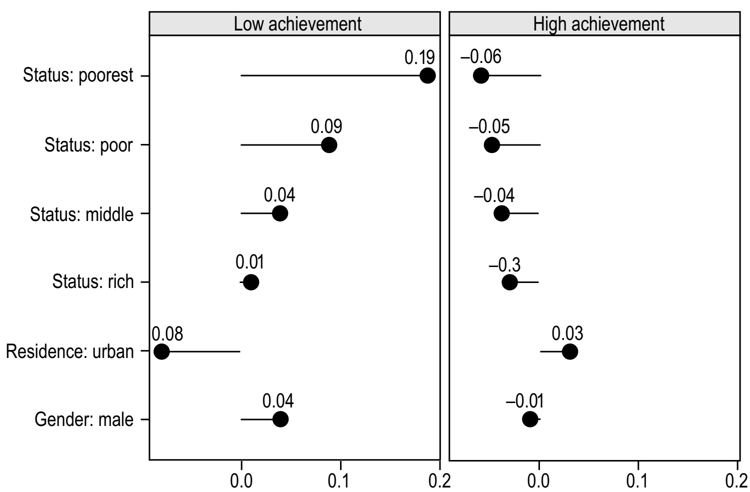
	Low academic achievement	High academic achievement	Growth mindset	Sense of belonging at school	Task mastery	Self-efficacy	Grit	Self-confidence
Status: poorest	1.42 (0.12)***	−2.03 (0.32)***	−0.7 (0.1)***	−0.59 (0.1)***	−0.8 (0.1)***	−0.91 (0.11)***	−0.18 (0.09)*	−0.22 (0.08)**
Status: poor	0.82 (0.12)***	−1.4 (0.24)***	−0.53 (0.09)***	−0.41 (0.09)***	−0.58 (0.1)***	−0.43 (0.1)***	−0.04 (0.09)	−0.22 (0.08)**
Status: middle	0.41 (0.13)**	−1.15 (0.21)***	−0.36 (0.09)***	−0.38 (0.09)***	−0.54 (0.1)***	−0.43 (0.1)***	−0.18 (0.09)*	−0.07 (0.08)
Status: rich	0.15 (0.14)	−0.6 (0.17)***	−0.34 (0.09)***	−0.27 (0.09)**	−0.34 (0.09)***	−0.34 (0.09)***	−0.04 (0.09)	−0.1 (0.08)
Residence: urban	−0.62 (0.08)***	1.27 (0.29)***	0.18 (0.08)*	−0.01 (0.08)	−0.16 (0.08)*	0 (0.08)	−0.19 (0.07)**	−0.04 (0.06)
Gender: male	0.33 (0.07)***	−0.27 (0.14)	0.21 (0.06)***	0.05 (0.06)	0.06 (0.06)	0.14 (0.06)*	−0.25 (0.05)***	0.53 (0.05)***
Intercept	−2.11 (0.12)***	−3.62 (0.3)***	−1.23 (0.1)***	−1.06 (0.1)***	−0.9 (0.1)***	−1.15 (0.1)***	−0.6 (0.09)***	−0.75 (0.08)***
Pseudo R^2 0,07	0.07	0.01	0.01	0.01	0.01	0.004	0.01	
N	6727	7063	6745	6570	6584	6614	6726	6601

Note. The following categories were chosen as the reference: richest for socio-economic status, rural for residence, and female for gender.

****p* < .0001; ***p* < .001; **p* < .01.

Source: authors' calculations based on the PISA 2018 data for Russia.

Figure 4. **Marginal Effects of the Predictor Variables on Belonging to High-Achieving and Low-Achieving Groups of Schoolchildren**



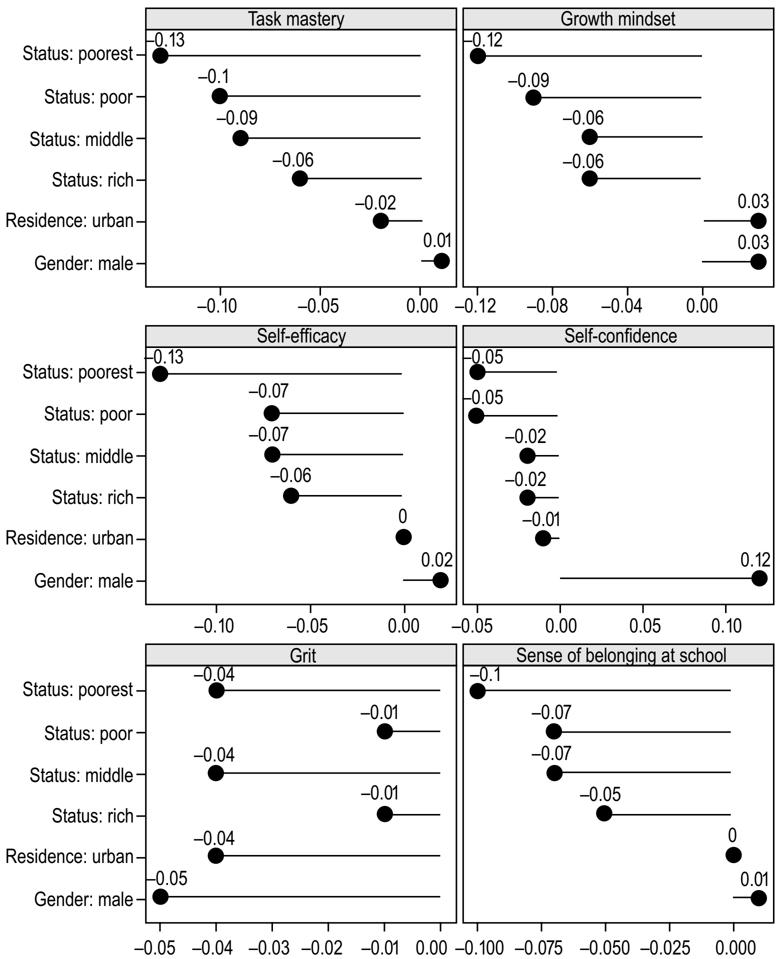
Note. The following categories were chosen as the reference: wealthiest for socio-economic status, rural for residence, and female for gender.

Source: authors' calculations based on the PISA 2018 data for Russia.

does not reach the minimum proficiency level in reading and mathematics is 19% higher for schoolchildren from the poorest families than for those from the wealthiest families. Schoolchildren from the poorest families are on average 10% less likely to be proficient in the six non-cognitive skills studied compared to children from the wealthiest families. The marginal effects are shown in Figure 5.

In order to answer the key research question of this paper — how strong is the effect of a schoolchild's non-cognitive skills on the probability of their belonging to those not reaching the minimum proficiency level in reading and mathematics, and how different is the effect of non-cognitive characteristics on academic achievement across socio-economic status groups — we conducted an analysis using propensity score matching. This method was chosen because it controls for sampling bias due to non-random

Figure 5. **Marginal Effect of Socio-Economic Status on Proficiency in Non-Cognitive Skills**



Note. The following categories were chosen as the reference: wealthiest for socio-economic status, rural for residence, and female for gender.

Source: authors' calculations based on the PISA 2018 data for Russia.

selection. The belonging to the group of schoolchildren with low academic achievement in reading and mathematics is a dependent variable (*Y*). A binary variable indicating whether a schoolchild has a high proficiency in a particular non-cognitive skill is the treatment variable (*W*). Socio-economic status, residence and gender of a child are control variables (X_n). To account for the heterogeneous effects of non-cognitive skills on low achievement across status groups, we introduced the interaction effect between a particular skill and socio-economic status.

Task mastery has a significant effect on the learning outcomes of schoolchildren, both in interaction with family socio-economic status and independently of it. While proficiency in this skill alone predicts up to a 6% probability of not joining the group of low achievers, when it interacts with the *poorest* category the probability becomes twice as high (12%). Self-confidence, self-efficacy or grit alone have no statistically significant effect on poor academic performance on average across the sample, but in interaction with socio-economic status, their effects increase, reaching their maxi-

Table 3. **Results of the Logistic Regression Models for Estimating the Impact of Non-Cognitive Skills and Socio-Economic Status on Low Academic Achievement (After Matching)**

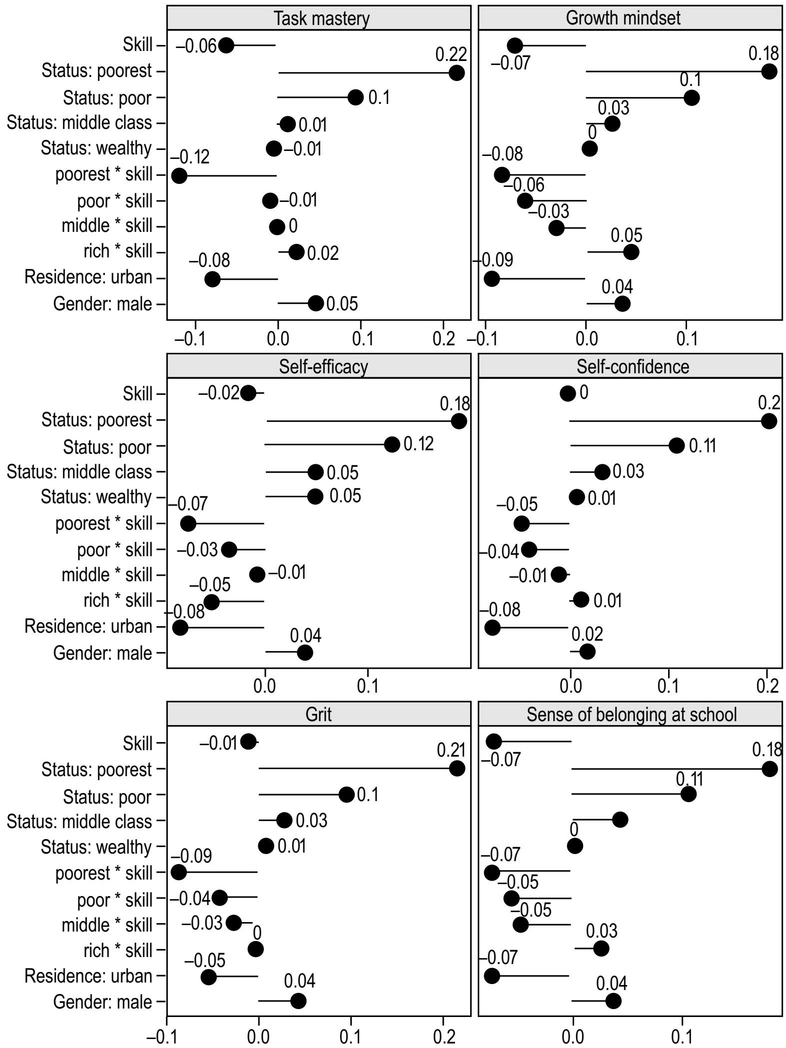
	Growth mindset	Sense of belonging at school	Task mastery	Self-efficacy	Grit	Self-confidence
Skill	−1.5 (0.37)***	−1.55 (0.39)***	−1.02 (0.3)***	−0.39 (0.31)	−0.18 (0.26)	−0.06 (0.24)
Status: poorest	1.24 (0.13)***	1.24 (0.13)***	1.37 (0.13)***	1.57 (0.15)***	1.6 (0.15)***	1.59 (0.16)***
Status: poor	0.86 (0.13)***	0.85 (0.13)***	0.74 (0.12)***	1.2 (0.14)***	0.94 (0.16)***	1.07 (0.17)***
Status: middle	0.28 (0.14)*	0.43 (0.14)**	0.13 (0.14)	0.66 (0.15)***	0.38 (0.18)*	0.46 (0.18)**
Status: rich	0.04 (0.14)	0.05 (0.15)	−0.05 (0.14)	0.67 (0.15)***	0.15 (0.18)	0.13 (0.19)
poorest * skill	0.57 (0.44)	0.69 (0.46)	−0.01 (0.38)	−0.17 (0.4)	−0.34 (0.3)	−0.2 (0.28)
poor * skill	0.32 (0.46)	0.49 (0.47)	0.52 (0.37)	0.02 (0.37)	−0.23 (0.32)	−0.27 (0.3)
middle * skill	−0.16 (0.54)	−0.11 (0.54)	0.26 (0.42)	0.12 (0.39)	−0.29 (0.36)	−0.11 (0.31)
rich * skill	1.17 (0.45)**	0.94 (0.48)	0.5 (0.4)	−0.54 (0.44)	−0.01 (0.35)	0.16 (0.33)
Residence: urban	−0.7 (0.09)***	−0.55 (0.08)***	−0.58 (0.08)***	−0.63 (0.09)***	−0.44 (0.08)***	−0.61 (0.08)***
Gender: male	0.36 (0.08)***	0.34 (0.08)***	0.41 (0.08)***	0.37 (0.08)***	0.41 (0.08)***	0.17 (0.08) *
Intercept	−1.86 (0.13)***	−1.97 (0.13)***	−1.89 (0.12)***	−2.37 (0.14)***	−2.37 (0.15)***	−2.37 (0.15)***
Pseudo R^2	0.08	0.07	0.07	0.07	0.07	0.07
N	5947	5947	5947	5947	5947	5947

Note. The following categories were chosen as the reference: wealthiest for socio-economic status, rural for residence, and female for gender.

****p* < .0001; **p < .001; *p < .01.

Source: authors' calculations based on the PISA 2018 data for Russia.

Figure 6. **Marginal Effects of Non-Cognitive Skills on Low Academic Achievement (After Matching)**



Note. The following categories were chosen as the reference: wealthiest for socio-economic status, rural for residence, and female for gender.

Source: authors' calculations based on the PISA 2018 data for Russia.

mums in schoolchildren from the poorest families and decreasing the probability of low achievement by 5%, 7%, and 9%, respectively. The marginal effect of having a growth mindset and a sense of belonging at school is equally strong in magnitude both on average across the sample and on students from the poorest families. This suggests a more universal role of these characteristics in reducing the proportion of poorly performing schoolchildren.

All models reveal significant effects of students' gender and residence. Boys are more likely (probability of up to 4% on average across all models) to become low achievers than girls. The statistically significant effect of residence emphasizes the issue of reaching the minimum proficiency level in reading and mathematics by schoolchildren from rural areas. Figure 6 shows marginal effects across all variables in the six models.

Limitations

This study has several limitations due to the specifics of the input data and analytical procedures applied. First, PISA is a program for comparative studies, and its research tools are adapted for more than 80 countries, meaning that the psychometric properties of tests used for assessing non-cognitive skills inevitably differ across contexts. Second, the PISA data are cross-sectional. To best assess the impact of non-cognitive skills on learning outcomes, large-scale longitudinal measurements need to be conducted. In this study, we apply the method of propensity score matching to calculate the effects of non-cognitive characteristics in a quasi-experimental manner, that is, without undertaking the interventions themselves. This leads to a third major limitation of this study — the extent to which the statistical data allow for pseudo-randomization of the observations. In other words, sampling bias may be stronger than what we can capture with the available variables used as confounders.

Fourth, according to the research design, the effects of non-cognitive skills on academic achievement are measured separately rather than together. However, these characteristics are not isolated from each other, and their combined impact should also be measured. The approach we have chosen is statistically justified, and, in economic logic, it is more informative for policy regulation. Figure 2 shows that non-cognitive characteristics are not strongly correlated. It means that the taxonomy of skills used in this study captures quite autonomous and stable personality traits. Although non-cognitive characteristics do not exist in isolation from one another, interventions in practice often focus on only one of them. The approach we have chosen allows us to evaluate in a quasi-experimental manner the effectiveness of potential interventions targeting individual skills. Given the weak correlation between the non-cognitive skills, we can assume that interventions aimed at developing one of them will have no significant effects on the others.

Finally, another notable limitation of the study is the loss of information due to the dichotomization of non-cognitive characteristics that were initially captured on a continuous scale. In econometrics, continuous variables are used when researchers are interested in elasticity, or the average coefficient of change. In particular, they might want to know how, on average, academic achievement will change when the score for a non-cognitive skill increases by one unit. In this study, however, we were interested in how the probability of low academic achievement would change if a schoolchild (particularly one from the poorest household) with a certain fixed set of control characteristics and low scores for non-cognitive skills had highly developed non-cognitive skills. The method of propensity score matching with the binarization of non-cognitive characteristics into treatment variables used in this study helps answer this question from a counterfactual perspective.

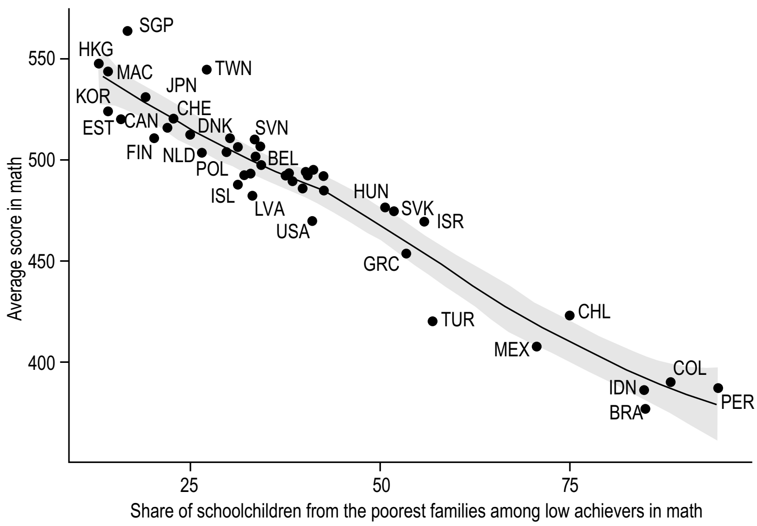
Discussion

This study, based on the econometric methods of causal analysis, provides a rationale for prioritizing interventions that support schoolchildren from families with low socio-economic status. This group of schoolchildren is the key focus of interventions aimed at developing effective and equitable education systems. Our analysis has confirmed a causal relationship between the socio-economic status of a child's family, their academic achievement, and proficiency in non-cognitive skills. Cross-country comparisons also reveal a strong statistical association between the phenomenon of low achievement among schoolchildren from the poorest families and the overall effectiveness of the education system. Figure 7 presents aggregate PISA scores [OECD, 2016b], which show that countries and territories where the majority of low achievers in mathematics come from the poorest families receive low average scores in PISA for this subject. There is a clearly identifiable cluster of countries and territories with less than 25% of low-achieving schoolchildren coming from the poorest families — and with the highest average scores. They are Hong Kong, Macao, Singapore, Taiwan, Finland and Estonia. Conversely, the countries where learners from the poorest families account for more than 75% of low achievers perform worst in educating schoolchildren. These countries are Indonesia, Colombia, Brazil and Peru. Thus, government support for the education of children from the poorest families can be considered one of the ways to ensure sustainable development of the education systems.

Public programs that focus on the development of non-cognitive skills can significantly improve the academic performance of schoolchildren, and the impact of investments in non-cognitive competencies will be greatest for the most vulnerable student groups — children from the poorest families. Although the current educational standard mentions non-cognitive skills as one of the priorities of general education, it lacks specific solutions for building and developing these competencies.

The experience of incorporating socio-emotional learning (SEL) programs into educational standards suggests that these programs have social and economic benefits beyond the education systems. For instance, a meta-analysis of 213 SEL programs implemented in preschools and schools around the world and involving more than 270,000 learners showed that participants in these programs sig-

Figure 7. **Scatter Plot: Average Mathematics Score by Country/Territory as a Function of the Proportion of Schoolchildren from the Poorest Families among Low Achievers in Mathematics**



Source: PISA 2015 aggregated cross-country scores.

nificantly increased their social and emotional competencies, which ultimately improved the quality of education at the macro-level [Durlak et al., 2011]. Moreover, these programs helped build positive relationships between teachers and students, which in its turn strengthened learners' attachment to school and contributed to a safe educational environment that encouraged prosocial behavior. Improving non-cognitive skills through SEL programs develops a positive sense of self in students and, in addition to enhancing academic performance, encourages prosocial behavior, contributes to addiction prevention, and improves their mental health [Sklad et al., 2012].

A benefit-cost analysis of SEL programs' effectiveness has confirmed that investments in these programs are economically justified [Lee et al., 2012; Jones et al., 2008; Miller, Hendrie, 2009]. For example, returns from New York City's three-year SEL program called 4Rs (Reading, Writing, Respect & Resolution), which focuses on non-cognitive skills, literacy, and aggression reduction in preschool and primary school children, are $1.2 million per 100 learners, while the program implementation costs are $55,000 per 100 learners [Jones et al., 2008; Belfield et al., 2015]. In the empirical studies of non-cognitive skills, economists focus on a social group often excluded from psychological research — the poorest population cohorts in developing countries [Wuepper, Lybbert, 2017].

Such support programs are critical for low-achieving schoolchildren at risk of dropping out of school, as without a completed secondary education these children might join the ranks of the unemployed [Dianda, 2008]. Transition from basic to secondary school is a nother phase of schooling that requires support programs for low achievers , as the learning challenges that arise during this period can lead to a major delay in human capital accumulation in adulthood [Yeager et al., 2019].

SEL programs targeting the development of specific skills have been implemented both at the micro-level (in individual schools) and at the national scale. For example, in Finland, targeted development of self-efficacy and task mastery improved the achievements of primary school students with poor numeracy skills [Koponen et al., 2021]. Self-efficacy intervention programs yielded positive results in promoting a healthy lifestyle and consumption culture among students with psychological barriers to physical activity [Lee, Arthur, Avis, 2008; Bouwman et al., 2020] as well as in addiction prevention [Hyde et al., 2008]. An economic program aimed at developing self-efficacy and improving self-esteem in children and adolescents from the urban slums of Mumbai resulted in a one standard deviation increase in self-efficacy and self-esteem measures; this increase in non-cognitive skills had an impact on students' final examination scores, choice of labor market strategies, and long-term goals [Krishnan, Krutikova, 2013].

Programs aimed at developing a sense of belonging have proved successful in cultivating an inclusive educational environment [Allen et al., 2021], which is especially relevant in multicultural Russian society. Developing a sense of belonging at school and a growth mindset in schoolchildren contributes to an inclusive and harmonious environment in educational institutions with ethnic and racial minorities [Walton, Cohen, 2011; 2007].

Implementing growth mindset interventions as part of educational programs is one of the most effective intervention strategies for students at risk of poverty, expulsion from school, underachievement, and social rejection. These programs are based on the belief that intelligence and skills can improve if students work hard at challenging tasks, seeing obstacles as an opportunity for effort and growth rather than as a failure [Paunesku et al., 2015]. An eight-hour course in growth mindset development taught by psychologists improved the mathematics scores of low-achieving 7th graders [Blackwell, Trzesniewski, Dweck, 2007]. As a result of extensive online training in growth mindset conducted for more than 1,000 learners in different geographic regions of the United States, the semester grades in key subjects of high school students increased, and the proportion of schoolchildren with failing grades decreased by 10%. The training proved particularly effective for students who were at risk of dropping out of school: in this group, the average standardized score in key subjects increased by 0.14 standard deviation after the training [Paunesku et al., 2015].

In the United States, an experiment with a nationwide sample of more than 6,000 high school students showed that an online, low-cost program in growth mindset development led to higher average scores in key subjects among low-achieving students at risk of poverty. In the academic literature, this experiment is the most extensive effort in implementing a growth mindset program that has produced results at the level of the entire education system rather than individual schools [Yeager et al., 2019].

In order to respond promptly to the challenges of time, the Russian education system must transform in accordance with the demands of the economy and society. The analysis undertaken in this paper suggests that there is a causal relationship between socio-economic status, learning outcomes, and non-cognitive skills of schoolchildren. Incorporating socio-emotional learning programs into a state educational standard of basic education is certainly not a universal solution to the problem of poverty and social exclusion in Russian or any other society. Still, the acquisition of key skills and competencies necessary to compete successfully in modern economies by at-risk schoolchildren can help them out of poverty by creating channels for upward social mobility. Integrated measures combining both economic policy and interventions aimed at the psychological factors of poverty are more effective than working exclusively with the institutional causes of poverty [Wuepper and Lybbert, 2017; Banerjee and Duflo, 2011; Banerjee et al., 2015].

Recommendations

Elimination of poverty and reduction of the risks associated with inequality refer to the key objectives of the public stakeholders with regards to the accumulation and reproduction of human capital. Effective education policy can make a significant contribution to the solution of this problem. The results of this study suggest that the development of certain non-cognitive skills in students can alleviate the effects of poverty on learning outcomes and thus contribute to reducing the inequalities reproduced in the education system. Programs for the development of non-cognitive skills should be deployed at the federal level as well as in the framework of regional and municipal initiatives and public-private partnerships.

While this article has examined the effects of such non-cognitive characteristics as growth mindset, grit, self-efficacy, sense of belonging at school, self-confidence, and task mastery, potential socio-emotional learning programs should also target characteristics not included in this taxonomy. The implementation of these programs requires further cooperation between psychologists and economists: the former should focus on research on key personality traits and approaches to their development, the latter on scaling up these initiatives to the regional and national levels, as well as measuring the benefits from developing these skills. Modernizing the education system by incorporating socio-emotional learning programs into the state standard of basic education will improve learning outcomes, creating positive triggers for the transformation of the socio-economic system.

It is needed to expand the value-normative basis of education policy and modernize it based on the principles of meritocracy. To achieve the targets of Sustainable Development Goal 4, it is necessary to accelerate the introduction of social inclusion into the education system, thus creating opportunities for the accumulation of human capital regardless of students' ascribed characteristics. In other words, educational programs should be adapted so that they ensure compensatory development of non-cognitive skills in children from vulnerable social groups to bridge the gap in learning outcomes between them and students from families with higher socio-economic status.

The modernization of the education system by including socio-emotional learning programs requires the development of a set of psychological techniques to facilitate program implementation and provide institutional support for groups with unconventional educational demands. Supplementary education and extracurricular programs, training and intensives focusing on the development of non-cognitive skills and targeting low achievers and children at risk of poverty will contribute to the transformation of the education system on the principles of social inclusion and equitable opportunities.

There is a gap in the education system between the special educational demands from socially and economically deprived groups and the ability of the education system to provide institutional mechanisms to meet these demands in a socially inclusive manner. In particular, there is a lack of skilled personnel: the education system urgently needs to revise the occupational standard of the school psychologist and social pedagogue, launch massive training programs for these jobs and form a new competence profile of general education staff.

These recommendations can be incorporated in the strategic planning documents being developed for education, such as the Concept of Teacher Training for the General Education System Until 2030. Whether students' performance can be improved in practice by investing in their non-cognitive skills will depend on how flexible the professional community and education policy makers will respond to the identified challenges.

The study was conducted with the financial support of the Southern Federal University in 2022, grant No. VnGr-07/2020-02-AP.

The authors would like to thank the anonymous reviewer for constructive feedback that helped improve the final version of the paper.

Appendix 1
Descriptive Statistics for Questions on Non-Cognitive Skills, %

No.	Question	Strongly disagree	Disagree	Agree	Strongly agree
	Growth mindset				
1	Your intelligence is something about you that you can't change very much	21	38	30	11
	Sense of belonging at school				
1	I feel like an outsider (or left out of things) at school	8	18	52	22
2	I make friends easily at school	14	54	26	6
3	I feel like I belong at school	14	57	24	5
4	I feel awkward and out of my place in my school	7	25	50	18
5	Other students seem to like me	11	52	30	7
6	I feel lonely at school	7	20	50	23
	Task mastery				
1	I find satisfaction in working as hard as I can	7	29	54	10
2	Once I start a task, I persist until it is finished.	4	24	56	16
3	Part of the enjoyment I get from doing things is when I improve on my past performance	4	15	66	15
4	If I am not good at something, I would rather keep struggling to master it than move on to something I may be good at	5	22	57	17
	Self-efficacy				
1	I usually manage one way or another	4	29	58	9
2	I feel proud that I have accomplished things	4	20%	62	14
3	I feel that I can handle many things at a time	4	35	52	9
4	My belief in myself gets me through hard times	5	20	59	16
5	When I'm in a difficult situation, I can usually find my way out of it	3	15	65	17
	Grit				
1	Trying hard at school will help me get a good job.	31	48	14	7
2	Trying hard at school will help me get into a good university (institute, college).	35	52	7	6
3	Trying hard at school is important.	28	49	16	7

No.	Question	Strongly disagree	Disagree	Agree	Strongly agree
	Fear of failure				
1	When I am failing, I worry about what others think of me.	14	33	42	11
2	When I am failing, I am afraid that I might not have enough talent.	13	39	39	9
3	When I am failing, this makes me doubt my plans for the future.	15	36	38	11

Source: authors' calculations based on the PISA 2018 data for Russia.

Appendix 2
Average Values of Standardized Scores for Non-Cognitive Skills by Gender, Residence and Socio-economic Status of Schoolchildren

Skills	Gender		Residence		Socio-economic status	
	Male	Female	Urban	Rural	Poorest 20%	Wealthiest 20%
Growth mindset	−0.03	0.03	0.02	−0.07	−0.1	0.07
Sense of belonging at school	0	0	0	0	−0.09	0.13
Task mastery	−0.01	0.01	−0.01	0.02	−0.11	0.17
Self-efficacy	0.04	−0.04	0.01	−0.04	−0.16	0.22
Grit	−0.07	0.07	−0.02	0.06	0.01	0
Self-confidence	0.13	−0.13	−0.01	0	−0.05	0.01
Reading	467.66	492.63	490.54	447.63	441.11	511.84
Mathematics	491.51	486.1	498.14	459.99	450.93	521.58

Note. Non-cognitive characteristics are standardized to the mean. General descriptive statistics for the sample are presented in Table 1 in the body of the article.

Source: authors' calculations based on the PISA 2018 data for Russia.

Appendix 3
Proportions of Schoolchildren With Well-Developed Non-Cognitive Skills and Poor Reading and Mathematics Skills, Total and by Their Gender, Residence and Socio-economic Status (%)

Skills	Total	Gender		Residence		Socio-economic status	
		Male	Female	Urban	Rural	Poorest 20%	Wealthiest 20%
Growth mindset*	19	21	18	20	16	15	26
Sense of belonging at school*	19	19	19	19	18	15	24
Task mastery*	18	18	18	18	18	13	25
Self-efficacy*	17	18	17	17	15	11	24
Grit*	26	24	29	25	28	26	28
Self-confidence*	32	37	27	32	32	30	35
Reading**	21	26	16	18	31	34	15
Mathematics***	19	19	19	16	29	34	10

* Schoolchildren with well-developed non-cognitive skills include all schoolchildren who have a value of 0.5 or higher on the scale standardized to the mean.
** Schoolchildren with poor reading and mathematics skills include all who score below a certain threshold on a standardized test in the OECD classification.

Source: authors' calculations based on the PISA 2018 data for Russia.

References

Abdollahi A., Noltemeyer A. (2018) Academic Hardiness: Mediator between Sense of Belonging to School and Academic Achievement? *The Journal of Educational Research*, vol. 111, no 3, pp. 345–351. doi:10.1080/00220671.2016.1261075

Akmal M., Pritchett L. (2021) Learning Equity Requires More Than Equality: Learning Goals and Achievement Gaps between the Rich and the Poor in Five Developing Countries*. International Journal of Educational Development*, vol. 82, April, Article no 102350. doi:10.1016/j.ijedudev.2021.102350

Allen K., Jamshidi N., Berger E., Reupert A., Wurf G., May F. (2021) Impact of School-Based Interventions for Building School Belonging in Adolescence: A Systematic Review. *Educational Psychology Review*, June, pp. 1–29. doi:10.1007/s10648-021-09621-w

Almlund M., Duckworth A., Heckman J., Kautz T. (2011) Personality Psychology and Economics. *Handbook of the Economics of Education* (eds E. Hanushek, S. Machin, L. Woessman), Amsterdam: Elsevier, vol. 4, ch. 1.

Attanasio O., Blundell R., Conti G., Mason G. (2020) *Inequality in Socio-Emotional Skills: A Cross-Cohort Comparison. IZA Discussion Papers no 13124*. Bonn: Institute of Labor Economics (IZA).

Bandura A. (1997) *Self-Efficacy: The Exercise of Control*. New York: W.H. Freeman.

Bandura A., Barbaranelli C., Caprara G.V., Pastorelli C. (2001) Self-Efficacy Beliefs as Shapers of Children's Aspirations and Career Trajectories. *Child Development*, vol. 72, no 1, pp. 187–206. doi:10.1111/1467-8624.00273

Banerjee A., Duflo E. (2011) Poor Economics. A Radical Rethinking of the Way to Fight Global Poverty. New York: Public Affairs. Available at: https://warwick.ac.uk/study/summer-with-warwick/warwick-summer-school/courses/macroeconomics/poor_economics.pdf (accessed 2 February 2022).

Banerjee A., Duflo E., Glennerster R., Kinnan C. (2015) The Miracle of Microfinance? Evidence from a Randomized Evaluation. *American Economic Journal: Applied Economics*, vol. 7, no 1, pp. 22–53. doi:10.2139/ssrn.2250500

Basu S., Meghani A., Siddiqi A. (2017) Evaluating the Health Impact of Large-Scale Public Policy Changes: Classical and Novel Approaches. *Annual Review of Public Health*, vol. 38, pp. 351–370. doi:10.1146/annurev-publhealth-031816-044208

Belfield C., Bowden A., Klapp A., Levin H., Shand R., Zander S. ((2015) The Economic Value of Social and Emotional Learning. *Journal of Benefit-Cost Analysis*, vol. 6, no 3, pp. 508–544. doi:10.1017/bca.2015.55

Blackwell L.S., Trzesniewski K.H., Dweck C.S. (2007) Implicit Theories of Intelligence Predict Achievement Across an Adolescent Transition: A Longitudinal Study and an Intervention. *Child Development*, vol. 78, no 1, pp. 246–263. doi:10.1111/j.1467-8624.2007.00995.x

Bouwman E., Onwezen M., Taufik D., de Buisonjé D., Ronteltap A. (2020) Brief Self-Efficacy Interventions to Increase Healthy Dietary Behaviours: Evidence from Two Randomized Controlled Trials. *British Food Journal*, vol. 122, no 11, pp. 3297–3311.

Broussard S.C., Garrison M.B. (2004) The Relationship between Classroom Motivation and Academic Achievement in Elementary-School-Aged Children. *Family and Consumer Sciences Research Journal*, vol. 33, no 2, pp. 106–120. doi:10.1177/1077727X04269573

Caliendo M., Kopeinig S. (2008) Some Practical Guidance for the Implementation of Propensity Score Matching. *Journal of Economic Surveys*, vol. 22, no 1, pp. 31–72. doi:10.1111/j.1467-6419.2007.00527.x

Chiapa C., Garrido J.L., Prina S. (2012) The Effect of Social Programs and Exposure to Professionals on the Educational Aspirations of the Poor. *Economics of Education Review*, vol. 31, no 5, pp. 778–798. doi:10.1016/j.econedurev.2012.05.006

Cinque M., Carretero S., Napierala J. (2021) *Non-Cognitive Skills and Other Related Concepts: Towards a Better Understanding of Similarities and Differences. JRC Working Papers on Labour, Education and Technology no 2021/09*. Seville: European Commission.

Claro S., Paunesku D., Dweck C. S. (2016) Growth Mindset Tempers the Effects of Poverty on Academic Achievement. *Proceedings of the National Academy of Sciences*, vol. 113, no 31, pp. 8664–8668. doi:10.1073/pnas.1608207113

Costa A., Faria L. (2018) Implicit Theories of Intelligence and Academic Achievement: A Meta-Analytic Review. *Frontiers in Psychology*, vol. 9, June, Article no 829. doi:10.3389/fpsyg.2018.00829

Crouch L., Rolleston C. (2017) *Raising the Floor on Learning Levels: Equitable Improvement Starts with the Tail. Research on Improving Systems of Education (RISE) Insights*. Available at: https://riseprogramme.org/sites/default/files/publications/RISE%20Equity%20Insight%20UPDATE.pdf (accessed 2 February 2022).

Crouch L., Rolleston C., Gustafsson M. (2021) *Eliminating Global Learning Poverty: The Importance of Equalities and Equity. RISE Working Paper no 21/079*. Available at: https://riseprogramme.org/sites/default/files/2021-09/Eliminating%20Global%20Learning%20Poverty-%20The%20Importance%20of%20Equalities%20and%20Equity.pdf (accessed 2 February 2022).

Danner D., Lechner C.M., Spengler M. (2021) Do We Need Socio-Emotional Skills? *Frontiers in Psychology*, vol. 12, August, Article no 723470. doi:10.3389/fpsyg.2021.723470

Dercon S., Krishnan P. (2009) Poverty and the Psychosocial Competencies of Children: Evidence from the Young Lives Sample in Four Developing Countries. *Children, Youth and Environments*, vol. 19, no 2, pp. 138–163.

Destin M., Hanselman P., Buontempo J., Tipton E., Yeager D. (2019) Do Student Mindsets Differ by Socioeconomic Status and Explain Disparities in Academic Achievement in the United States? *AERA Open*, vol. 5, no 3, pp. 1–12. doi:10.1177/2332858419857706

Dianda M.R. (2008) *Preventing Future High School Dropouts: An Advocacy and Action Guide for NEA State and Local Affiliates*. Washington: NEA.

Duckworth A. (2016) *Grit: The Power of Passion and Perseverance*. New York: Scribner.

Durlak J., Weissberg R., Dymnicki A., Taylor R., Schellinger K. (2011) The Impact of Enhancing Students' Social and Emotional Learning: A Meta-Analysis of School-Based Universal Interventions. *Child Development*, vol. 82, no 1, pp. 405–432. doi:10.1111/j.1467-8624.2010.01564.x

Essama-Nssah B. (2006) *Propensity Score Matching and Policy Impact Analysis: A Demonstration in EViews. World Bank Policy Research Working Paper no 3877*. Available at: https://openknowledge.worldbank.org/bitstream/handle/10986/8730/wps38770rev0pdf.pdf?sequence=1 (accessed 2 February 2022).

Farah M. J. (2017) The Neuroscience of Socioeconomic Status: Correlates, Causes, and Consequences. *Neuron*, vol. 96, no 1, pp. 56–71. doi:10.1016/j.neuron.2017.08.034

Farrington C.A., Roderick M., Allensworth E., Nagaoka J. et al. (2012) *Teaching Adolescents to Become Learners: The Role of Noncognitive Factors in Shaping School Performance—A Critical Literature Review*. Chicago: University of Chicago Consortium on Chicago School Research. Available at: https://www.kipp.org/wp-content/uploads/2016/11/Teaching_Adolescents_to_Become_Learners.pdf (accessed 2 February 2022).

Garcia E. (2016) The Need to Address Non-Cognitive Skills in the Education Policy Agenda. *Non-Cognitive Skills and Factors in Educational Attainment* (eds M.S. Khine, S. Areepattamannil), Dordrecht: Sense, pp. 31–64.

Gimpelson V.E., Zudina A.A., Kapeliushnikov R.I. (2020) Nekognitivnye komponenty chelovecheskogo kapitala: chto govoryat rossiyskie dannye [Non-Cognitive Components of Human Capital: Evidence from Russian Data]. *Voprosy Ekonomiki*, no 11, pp. 5–31. doi: 10.32609/0042-8736-2020-11-5-31

Goodenow C. (1993) Classroom Belonging among Early Adolescent Students: Relationships to Motivation and Achievement. *The Journal of Early Adolescence*, vol. 13, no 1, pp. 21-43. doi:10.1177/0272431693013001002

Heckman J.J. (2006) Skill Formation and the Economics of Investing in Disadvantaged Children. *Science*, vol. 312, no 5782, pp. 1900–1902. doi:10.1126/science.1128898

Heckman J.J. (2000) Policies to Foster Human Capital. *Research in Economics*, vol. 54, no 1, pp. 3–56. doi:10.1006/reec.1999.0225

Heckman J.J., Kautz T. (2014) Fostering and Measuring Skills: Interventions that Improve Character and Cognition. *The Myth of Achievement Tests: The GED and the Role of Character in American Life* (eds J.J. Heckman, J.E. Humphries, T. Kautz), Chicago, IL: University of Chicago. doi:10.7208/chicago/9780226100128.003.0009

Heinrich C., Maffioli A., Vazquez G. (2010) *A Primer for Applying Propensity-Score Matching. Impact-Evaluation Guidelines. Inter-American Development Bank Technical Notes no IDB-TN-161*. Available at: https://publications.iadb.org/publications/english/document/A-Primer-for-Applying-Propensity-Score-Matching.pdf (accessed 2 February 2022).

Humphries J.E., Kosse F. (2017) On the Interpretation of Non-Cognitive Skills–What Is Being Measured and Why It Matters. *Journal of Economic Behavior & Organization*, vol. 136, April, pp. 174–185. doi:10.1016/j.jebo.2017.02.001

Hwang M.H., Choi H.C., Lee A., Culver J.D., Hutchison B. (2016) The Relationship between Self-Efficacy and Academic Achievement: A 5-Year Panel Analysis. *The Asia-Pacific Education Researcher*, vol. 25, no 1, pp. 89–98. doi:10.1007/s40299-015-0236-3

Hyde J., Hankins M., Deale A., Marteau T. (2008) Interventions to Increase Self-Efficacy in the Context of Addiction Behaviours: A Systematic Literature Review. *Journal of Health Psychology*, vol. 13, no 5, pp. 607–623. doi:10.1177/1359105308090933

Jones D., Bumbarger B., Greenberg M., Greenwood P., Kyler S. (2008) *PCCD's Investment in Research-Based Programs: A Cost-Benefit Assessment of Delinquency Prevention in Pennsylvania*. Pennsylvania: Pennsylvania State University.

Józsa K., Molnár E.D. (2013) The Relationship between Mastery Motivation, Self-Regulated Learning, and School Success: A Hungarian and Wider European Perspective. *Handbook of Self-Regulatory Processes in Development: New Directions and International Perspectives* (eds K.C. Barrett, N.A. Fox, G.A. Morgan, D.A. Fidler, L.A. Daunhauer), New York: Psychology Press, pp. 265–304.

Józsa K., Kis N., Barrett K.C. (2019) Mastery Motivation, Parenting, and School Achievement among Hungarian Adolescents. *European Journal of Psychology of Education*, vol. 34, no 2, pp. 317–339. doi:10.1007/s10212-018-0395-8

Kankaraš M., Suarez-Alvarez J. (2019) *Assessment Framework of the OECD Study on Social and Emotional Skills*. Paris: OECD.

Knudsen E.I., Heckman J.J., Cameron J.L., Shonkoff J.P. (2006) Economic, Neurobiological, and Behavioral Perspectives on Building America's Future Workforce. *Proceedings of the National Academy of Sciences*, vol. 103, no 27, pp. 10155–10162.

Koch A., Nafziger J., Nielsen H. S. (2015) Behavioral Economics of Education. *Journal of Economic Behavior & Organization*, vol. 115, July, pp. 3–17. doi:10.1016/j.jebo.2014.09.005

Komarraju M., Nadler D. (2013) Self-Efficacy and Academic Achievement: Why Do Implicit Beliefs, Goals, and Effort Regulation Matter? *Learning and Individual Differences*, vol. 25, June, pp. 67–72. doi:10.1016/j.lindif.2013.01.005

Koponen T., Aro T., Peura P., Leskinen M., Viholainen H., Aro M. (2021) Benefits of Integrating an Explicit Self-Efficacy Intervention with Calculation Strategy Training for Low-Performing Elementary Students. *Frontiers in Psychology*, vol. 12, August, Article no 3298. doi:10.3389/fpsyg.2021.714379

Köseoglu Y. (2015) Self-Efficacy and Academic Achievement—A Case from Turkey. *Journal of Education and Practice*, vol. 6, no 29, pp. 131–141.

Krishnan P., Krutikova S. (2013) Non-Cognitive Skill Formation in Poor Neighbourhoods of Urban India. *Labour Economics*, vol. 24, October, pp. 68–85. doi:10.1016/j.labeco.2013.06.004

Kuzminov Ya.I., Sorokin P.S., Froumin I.D. (2019) Obshchie i spetsial'nye navyki kak komponenty chelovecheskogo kapitala: chto govoryat rossiyskie dannye [Generic and Specific Skills as Components of Human Capital: New Challenges for Education Theory and Practice]. *Foresight and STI Governance*, vol. 13, no 2, pp. 19–41. doi:10.17323/2500-2597.2019.2.19.41

Laker D.R., Powell J.L. (2011) The Differences between Hard and Soft Skills and Their Relative Impact on Training Transfer. *Human Resource Development Quarterly*, vol. 22, no 1, pp. 111–122. doi:10.1002/hrdq.20063

Lam K.K.L., Zhou M. (2019) Examining the Relationship between Grit and Academic Achievement within K-12 and Higher Education: A Systematic Review. *Psychology in the Schools*, vol. 56, no 10, pp. 1654–1686. doi:10.1002/pits.22302

Lee J. (2020) *Non-Cognitive Characteristics and Academic Achievement in Southeast Asian Countries Based on PISA 2009, 2012, and 2015. OECD Education Working Paper no 233*. Available at: https://www.oecd-ilibrary.org/docserver/c3626e2f-en.pdf?expires=1643647473&id=id&accname=guest&checksum=13843AA81BC429A1ED63D2A50D9B539A (accessed 2 February 2022).

Lee L.L., Arthur A., Avis M. (2008) Using Self-Efficacy Theory to Develop Interventions That Help Older People Overcome Psychological Barriers to Physical Activity: A Discussion Paper. *International Journal of Nursing Studies*, Vol. 45. No 11. P. 1690–1699. doi:10.1016/j.ijnurstu.2008.02.012

Lee S., Aos S., Drake E., Pennucci A., Miller M., Anderson L., Burley M. (2012*) Return on Investment: Evidence-Based Options to Improve State-Wide Outcomes. Technical Appendix Methods and User Manual*. Olympia, WA: Washington State Institute for Public Policy. Available at: https://www.wsipp.wa.gov/ReportFile/1387 (accessed 2 February 2022).

Lee S., Sohn Y.W. (2017) Effects of Grit on Academic Achievement and Career-Related Attitudes of College Students in Korea. *Social Behavior and Personality: An International Journal*, vol. 45, no 10, pp. 1629–1642. doi:10.2224/sbp.6400

Lipnevich A.A., MacCann C., Roberts R.D. (2013) Assessing Non-Cognitive Constructs in Education: A Review of Traditional and Innovative Approaches. *The Oxford Handbook of Child Psychological Assessment* (eds D.N. Saklofske, C.R. Reynolds, V.L. Schwean), Oxford: Oxford University, pp. 750–772. doi: 10.1093/oxfordhb/9780199796304.013.0033

Maksimova M.A. (2019) The Return to Non-Cognitive Skills on the Russian Labor Market. *Applied Econometrics / Prikladnaya ekonometrika*, vol. 53, pp. 55–72.

Miller T., Hendrie D. (2009) *Substance Abuse Prevention Dollars and Cents: A Cost-Benefit Analysis. DHHS Publication No (SMA) 07-4298*. Available at: https://www.samhsa.gov/sites/default/files/cost-benefits-prevention.pdf (accessed 2 February 2022).

OECD (2021a) Can a Growth Mindset Help Disadvantaged Students Close the Gap? *PISA in focus*. Vol. 112. Available at: https://www.oecd-ilibrary.org/docserver/20922f0d-en.pdf?expires=1643469950&id=id&accname=guest&checksum=E5C199FFFEDADFC19A9208BA49301DAE (accessed 2 February 2022).

OECD (2021b) *Survey on Social and Emotional Skills (SSES): Moscow (The Russian Federation)*. Paris: OECD. Available at: https://www.oecd-ilibrary.org/docserver/6f28a4f0-en.pdf?expires=1643470120&id=id&accname=guest&checksum=9D951245886E7D290D018CA2E7688AA8 (accessed 2 February 2022).

OECD (2019) Education at a Glance 2019: OECD Indicators. Paris: OECD. Available at: https://www.oecd-ilibrary.org/education/education-at-a-glance-2019_f8d7880d-en (accessed 2 February 2022).

OECD (2018) Education at a Glance 2018: OECD Indicators. Paris: OECD. Available at: https://www.oecd-ilibrary.org/education/education-at-a-glance-2018_eag-2018-en (accessed 2 February 2022).

OECD (2017) PISA 2015 Results. Vol. III. Students' Well-Being. Paris: OECD. Available at: https://www.oecd.org/pisa/PISA-2015-Results-Students-Well-being-Volume-III-Overview.pdf (accessed 2 February 2022).

OECD (2016a) Low-Performing Students: Why They Fall Behind and How to Help Them Succeed. Paris: OECD. Available at: https://www.oecd-ilibrary.org/education/low-performing-students_9789264250246-en (accessed 2 February 2022).

OECD (2016b) PISA 2015 Results. Vol. I: Excellence and Equity in Education. Paris: OECD. Available at: https://www.oecd-ilibrary.org/education/pisa-2015-results-volume-i_9789264266490-en(accessed 2 February 2022).

Pasquier-Doumer L., Brandon F.R. (2015) Aspiration Failure: A Poverty Trap for Indigenous Children in Peru? *World Development*, vol. 72, no 2015, pp. 208–223. doi:10.1016/j.worlddev.2015.03.001

Paunesku D., Walton G.M., Romero C., Smith E., Yeager D., Dweck C. (2015) Mind-Set Interventions Are a Scalable Treatment for Academic Underachievement. *Psychological Science*, vol. 26, no 6, pp. 784–793. doi:10.1177/0956797615571017

Rozhkova K.V. (2019) Otdacha ot nekognitivnykh kharakteristik na rossiyskom rynke truda [The Return to Noncognitive Characteristics in the Russian Labor Market]. *Voprosy Ekonomiki*, no 11, pp. 81–107. doi: 10.32609/0042-8736-2019-11-81-107

Rozhkova K. V., Roshchin S. Yu. (2021a) Vliyanie nekognitivnykh kharakteristik na vybor traektoriy v vysshem obrazovanii: vzglyad ekonomistov [The Impact of Non-Cognitive Characteristics on the Higher Education Choice-Making: An Economist Perspective]. *Voprosy obrazovaniya / Educational Studies Moscow*, no 3, pp. 138–167. doi: 10.17323/1814-9545-2021-3-138-167

Rozhkova K. V., Roshchin S. Y. (2021b) Nekognitivnye kharakteristiki i vybor v sfere vysshego obrazovaniya [Non-Cognitive Characteristics and Higher Education Choices]. *Voprosy obrazovaniya / Educational Studies Moscow*, no 4, pp. 35–73. doi: 10.17323/1814-9545-2021-4-35-73

Schmidt F., Lindner C., Etzel J., Retelsdorf J. (2020) Self-Control Outdoes Fluid Reasoning in Explaining Vocational and Academic Performance—But Does It? *Frontiers in Psychology*, vol. 11, Article no 757. doi:10.3389/fpsyg.2020.00757

Shook N.J., Clay R. (2012) Interracial Roommate Relationships: A Mechanism for Promoting Sense of Belonging at University and Academic Performance. *Journal of Experimental Social Psychology*, vol. 48, no 5, pp. 1168–1172. doi:10.1016/j.jesp.2012.05.005

Sklad M., Diekstra R., Ritter M., Ben J., Gravesteijn C. (2012) Effectiveness of School-Based Universal Social, Emotional, and Behavioral Programs: Do They Enhance Students' Development in the Area of Skill, Behavior, and Adjustment? *Psychology in the Schools*, vol. 49, no 9, pp. 892–909. doi:10.1002/pits.21641

Steinmayr R., Weidinger A., Schwinger M., Spinath B. (2019) The Importance of Students' Motivation for Their Academic Achievement–Replicating and Extending Previous Findings. *Frontiers in Psychology*, vol. 10, July, Article no 1730. doi:10.3389/fpsyg.2019.01730

Stumm von S., Plomin R. (2015) Socioeconomic Status and the Growth of Intelligence from Infancy through Adolescence. *Intelligence*, vol. 48, February, pp. 30–36. doi:10.1016/j.intell.2014.10.002

Suprayogi M.N., Ratriana L., Wulandari A.P.J. (2019) The Interplay of Academic Efficacy and Goal Orientation toward Academic Achievement. *Journal of Physics: Conference Series*, vol. 1175, Article no 012132.

Tafere Y. (2014) *Young Lives Working Paper 120. Education Aspirations and Barriers to Achievement for Young People in Ethiopia*. Oxford: Young Lives, Department of International Development at the University of Oxford.

Urvashi D., Singh A. (2017) Non-Cognitive Skills as Essential Life-Skills for School Students. *International Journal of Recent Scientific Research*, vol. 8, iss. 9, pp. 20378–20381.

Vukasović T., Bratko D. (2015) Heritability of Personality: A Meta-Analysis of Behavior Genetic Studies. *Psychological Bulletin*, vol. 141, no 4, pp. 769–785. doi:10.1037/bul0000017

Wanzer D., Postlewaite E., Zargarpour N. (2019) Relationships among Noncognitive Factors and Academic Performance: Testing the University of Chicago Consortium on School Research Model. *AERA Open*, vol. 5, no 4, pp. 1–20. doi:10.1177/2332858419897275

Walton G. M., Cohen G. L. (2011) A Brief Social-Belonging Intervention Improves Academic and Health Outcomes of Minority Students. *Science*, vol. 331, no 6023, pp. 1447–1451. doi:10.1126/science.1198364

Walton G. M., Cohen G. L. (2007) A Question of Belonging: Race, Social Fit, and Achievement. *Journal of Personality and Social Psychology*, vol. 92, no 1, pp. 82–96. doi:10.1037/0022-3514.92.1.82

Wolters C.A., Hussain M. (2015) Investigating Grit and Its Relations with College Students' Self-Regulated Learning and Academic Achievement. *Metacognition and Learning*, vol. 10, no 3, pp. 293–311. doi:10.1007/s11409-014-9128-9

Wuepper D., Lybbert T.J. (2017) Perceived Self-Efficacy, Poverty, and Economic Development. *Annual Review of Resource Economics*, vol. 9, pp. 383–404. doi:10.1146/annurev-resource-100516-053709

Wuepper D., Sauer J. (2016) Explaining the Performance of Contract Farming in Ghana: The Role of Self-Efficacy and Social Capital. *Food Policy*, vol. 62, March, pp. 11–27.

Yeager D., Hanselman P., Walton G. et al. (2019) A National Experiment Reveals Where a Growth Mindset Improves Achievement. *Nature*, vol. 573, no 7774, pp. 364–369. doi:10.1038/s41586-019-1466-y

Zhou K. (2017) Non-Cognitive Skills: Potential Candidates for Global Measurement. *European Journal of Education*, vol. 52, no 4, pp. 487–497. doi:10.1111/ejed.12241