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Pınar Karaman[1]
[1] Sinop University, 0000-0002-2218-2701

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Examining Non-cognitive Factors Predicting Reading Achievement in Turkey: Evidence from PISA 2018

Pınar Karaman[1*]
[1]Sinop University

Abstract

The purpose of the study was to investigate how student and teacher-related non-cognitive variables were important factors in the reading performances of Turkish students in PISA 2018. The results of the HLM analysis revealed that economic, social, and cultural status (ESCS) as a background variable was considered an effective predictor of student and school reading achievement. The students' meta-cognitive strategies were the most influential variables among their non-cognitive variables. Besides, most of the teacher-related non-cognitive factors had significant relationships with reading achievement even after controlling all student-related and background variables. Teachers' instructional behaviors, such as adaptive instruction and teacher-directed instruction, are much more related to reading performance than other teacher behaviors. The results suggested that fostering soft skills is essential for both students and teachers.

Keywords: Reading Achievement, Meta-cognitive strategies, Adaptive instruction, Teacher-directed instruction, Hierarchical linear models

Introduction

Non-cognitive outcomes are equally important as cognitive outcomes in education. These two fundamental human competencies are influential in the 21st century. Non-cognitive competencies have a vital role in success in school, work, and life (Gabrieli et al., 2015). Certain types of non-cognitive skills play a crucial role in improving cognitive skills, academic achievement, and education systems (Aksu & Güzeller, 2016; Heckman et al., 2006; Gabrieli et al., 2015; Gamazo & Martinez-Abad, 2020; Khine & Areepattamannil, 2016; OECD, 2019a, 2019b). Non-cognitive or soft skills represent personal attributes and skills. Non-cognitive factors, also used as a broader term, include behaviors, attitudes, and strategies. This construct represents several psychosocial dispositions such as beliefs, attitudes, self-efficacy, meta-cognitive strategies, behaviors, emotions, and motivation. These skills have two main categories: intrapersonal (human attributes of how they manage themselves) and interpersonal (how they interact with others) (Gabrieli et al., 2015). Psychological and emotional attributes that influence student learning are easily affected by change from environmental factors, experiences, and social interactions (Lee & Shute, 2010).

Traditionally, the importance of the development of students' cognitive skills, such as academic skills and content knowledge, is focused intensely (Wanzer et al., 2019). For instance, the studies include the effects of psychometric intelligence (Furnham et al., 2006; Hannon, 2016; Malhotra, 2020); the effect of working memory (Bergman Nutley & Söderqvist, 2017; Çalışkanel, 2013; Swanson & Alloway, 2012) on academic performance and learning. However, cognitive factors are not the only factors that influence academic achievement (Cunha & Heckman, 2008; Lee & Shute, 2010). Non-cognitive factors representing students' characteristics such as their behaviors, attitudes, and personalities are also main determinants of achievement (Allen et al., 2009; Fonteyne et al., 2017). Non-cognitive factors consist of several constructs. Background factors, attitudes, interests, coping skills and strategies, thinking style, temperament are potential lists of non-cognitive factors (Messick, 1979). Self-concept, self-efficacy, attitudes, personality, learning process, social and emotional skills are also classified as non-cognitive factors (Lipnevich & Roberts, 2012; Sedlacek, 2010). It shows that the classification of non-cognitive constructs is not all clear (Fonteyne et al., 2017).

* Corresponding Author: *Pınar Karaman, pkaraman1626@gmail.com*

A growing number of studies indicate that non-cognitive variables have been shown to impact on academic achievement (Gutman & Schoon, 2013; Hattie, 2009; Lee & Shute, 2010; Lee & Stankov, 2018; Wanzer et al., 2019). Hattie (2009) synthesized almost 800 studies through meta-analysis. The results showed that engagement, motivation, self-concept, anxiety, and attitude towards mathematics were the strongest non-cognitive predictors of academic achievement. Lee & Shute's (2010) literature review indicated that achievement is not only affected by cognitive factors but that motivational, affective, and contextual factors are also important. The results of the study showed that various variables were related to students' academic achievement at K-12 school levels. They grouped psychological constructs into four major domains. These domains are: (1) student engagement including behavioral, cognitive-motivational, and emotional engagement; (2) learning strategies including cognition, metacognition, and behaviors; and (3) school climate-related social-contextual factors such as teacher interaction, school atmosphere, and (4) social-familial impacts consisting of parents' and peers' motivation, affect, and behaviors. Farrington et al. (2012) also suggested that five general categories of non-cognitive factors (academic behaviors, academic perseverance, academic mindsets, learning strategies, and social skills) are associated with academic performance. In particular, teachers have a crucial role in students' achievement and their attitudes toward school (OECD, 2019a, 2019b; Yıldırım, 2012). According to the expectancy-value model, teachers' behaviors positively affect student motivational beliefs and academic achievement (Wigfield & Eccles, 2000). Teachers' support such as encouraging and helping students with their learning, making them progress, and giving opportunities to express themselves in classroom activities (OECD, 2019a; Klem & Connell, 2004). Besides, teachers' effective instructional practices such as providing clear learning goals, encouraging students to talk about their thinking, and providing feedback to students on their progress are essential for student motivation and learning (Popham, 2000; Tyler, 2000).

International Large-Scale Assessments

International large scale assessments such as Programme for International Student Assessment (PISA), Trends in International Mathematics and Science Study (TIMSS), or Progress in International Reading Literacy Study (PIRLS) have a significant impact on educational research studies, and also national policies and practices (Gamazo & Martinez-Abad, 2020; Lingard et al., 2013). These assessments allow educational researchers to study deeply the databases that are reported by the OECD. International large-scale assessments have mainly focused on cognitive assessment (Klieme, 2016; Wu, 2010). However, non-cognitive outcomes have been less focused on these assessments (He et al., 2019). These assessments administered to students, teachers and principals in PISA and TIMMS surveys provide to understand the influences of contexts and factors on student learning (Ersan & Rodriguez, 2020; He et al., 2019; Mullis & Martin, 2013). Self-reported likert scale items are administered to measure non-cognitive factors in these large-scale surveys. Lee and Stankov (2018) examined the relationship between non-cognitive variables and academic achievement in TIMMS and PISA. They found that self-efficacy variable in PISA and confidence variable in TIMMS were the strong predictors of student math achievement. Besides, educational aspiration in both PISA and TIMSS was also the best predictor of student math achievement. Moreover, Ma et al. (2021) examined the effects of perceived teacher support and motivational beliefs on student reading performance by using a multilevel mediation model in the Chinese sample of PISA 2018. Their results indicated that teacher support and motivational beliefs are important predictors of student learning. Overall, the results showed that non-cognitive factors have a crucial role in academic achievement. Given the literature, the studies delve deeper into databases to investigate relationships among non-cognitive variables by using different methods that are unreported by the OECD. Investigating the effects of different types of non-cognitive factors is crucial due to their potential positive influences on student academic achievement. Thus, the purpose of the present study was to explore the relationship between non-cognitive factors and reading achievement in the Turkish sample of PISA 2018. It is expected that research findings can help to better understand non-cognitive factors in predicting student achievement in Turkey by using a multi-level model.

Method

This study has a cross-sectional design that examines the relationship between student reading achievement and student-related variables in the PISA 2018 dataset.

The Database and Sample

PISA (International Student Assessment OECD Programme) periodically assesses and monitors 15-year-old students' knowledge and skills at the end of their compulsory education (OECD, 2019a). The PISA assessment design randomly samples 15-year-old students from each school. The survey gathers questionnaire data only from students. Students participating in PISA not only respond to questions about reading, mathematics, and science but also about themselves, their teachers' teaching qualities and practices, and their schools.

PISA measures students' performances in three main domains: reading literacy, mathematics literacy, and science literacy. Reading literacy was the major domain of assessment in PISA 2018. The student level and school level data for the present study were collected from the PISA 2018 database for Turkey. 6890 students from Turkey have participated in PISA 2018. However, missing values exist in selected factors for the present study. Hence, 6850 15-year-old students from 186 schools were sampled to represent the target population for analysis after exluding missing values.

Measures

The outcome measure for the study was student reading achievement as measured by reading literacy in PISA 2018. The research included some of the non-cognitive variables to address the relationship between reading literacy and non-cognitive factors in the dataset. The variables categorized into major research factors are described in Table 1 (Farrington et al., 2012; Lee & Stankov, 2018). Several students' non-cognitive variables like reading enjoyment, disciplinary climate, and meta-cognitive strategies as provided in Table 1 were included in the study. ESCS refers to family economic, social, and cultural status was used as a student background variable. Teacher related non-cognitive variables representing teacher behavior such as adaptive instruction, teacher support, and teacher feedback were also included in the study.

Table 1. Description of non-cognitive factors in PISA 2018

Factors	Non-cognitive variables and variable labels in the PISA 2018 database
Affect	Enjoyment of reading (JOYREAD)
School Climate	Disciplinary climate (DISCLIMA), Perception of competitiveness at school (PERCOMP), Perception of cooperation at school (PERCOOP)
Personality	Sense of belonging to school (BELONG)
Planned Behavior	Attitude towards school: Learning activities (ATTLNACT)
Learning Strategies	Metacognitive awareness about reading strategies: summarizing (METASUM), understanding and remembering (UNDREM), assessing credibility (METASPAM)
Self-beliefs	Self-efficacy (resilience) (RESILIENCE), Self-concept of reading: perception of competence (SCREADCOMP) and perception of difficulty (SCREADDIFF)
Motivation	Competitiveness (COMPETE), Mastery of Goal orientation (MASTGOAL), Work mastery (WORKMAST), Fear of failure (GFOFAIL)
Teacher Behavior	Adaptive instruction (ADAPTIVITY), Teacher-directed instruction (DIRINS), Teacher support (TEACHSUP), Teacher enthusiasm (TEACHINT), Teacher feedback (PERFEED), Teachers' stimulation of reading engagement (STIMREAD)

Statistical Analyses

First of all, descriptive statistics were used to examine all variables. Since PISA data has a nested structure where students are nested within schools, multilevel analysis was conducted by using hierarchical linear modeling (HLM) (Raudenbush & Bryk, 2002). This approach is suitable for several reasons (Raudenbush & Sampson, 1999): the multi-level design model helps to handle unbalanced large-scale data, includes all information from the data set, estimates all parameters, and measures predictors without error. P-P plots were examined at Level 1 and Level 2 for normality assumptions in PISA 2018 for Turkey dataset. It showed that the assumption was not violated.

Reading literacy as a dependent variable was measured in 10 plausible values estimated with item response theory (IRT): understanding, evaluating, reflecting, and engaging with texts (OECD, 2019a). To estimate reading literacy, each of ten data sets for reading literacy (ten plausible values) as an outcome was measured in the study. The IDB analyzer (OECD 2016a) was used to get syntax for all plausible values and weights. HLM 8 (Raudenbush et al., 2019) was employed for hierarchical linear modeling.

A two-level HLM was conducted in the present study. The analysis consisted of three stages. At the first stage, a one-way analysis of variance model (null model) was conducted to allow partitioning of reading performance into within and between school variances. Intra Class Correlation (ICC) value was calculated for the null model to determine whether HLM analysis was suitable for the data. In Model 1, the variables of students' non-cognitive factors and student ESCS as background variable at the student level and school average ESCS at the school level were added. Model 2 was extended to include the variables of teacher-related factors at the student level and school-average ESCS at the school level. Ultimately, all student, teacher, and school-related factors were included in the full model.

Results

Descriptive Statistics

According to the original PISA 2018 dataset for Turkey, 6890 students and 189 schools exist in the sample. After cases with missing values were excluded from the dataset, the final sample of the data had 6850 students with 186 schools. Table 2 indicates the descriptive statistics for students, teachers, and school characteristics. PISA 2018 questionnaires with a mean of 0 and a standard deviation of 1 scale index for OECD countries (OECD, 2017). Negative scores show that students responded more negatively than the average student across OECD countries. Turkish students more negatively responded than the average student across countries' characteristics for most of the non-cognitive factors and background variable (ESCS). However, they responded more positively than the OECD average for most of the teacher-related factors.

Table 2. Descriptive statistics at student level and school level variables

Student Level Variables (Level 1) (N=6850)	M	SD	Min	Max
ESCS	-1.71	1.17	-4.75	2.76
Reading enjoyment	0.68	0.97	-2.73	2.65
Motivation to master tasks	0.01	1.09	-2.73	1.81
Fear of failure	0.11	1.00	-1.89	1.89
Mastery Goal Orientation	-0.05	1.12	-2.52	1.85
Competitiveness	0.32	1.21	-2.34	2.00
Self efficacy	0.35	1.14	-3.16	2.36
Self-concept of reading: perception of competence	0.02	0.97	-2.44	1.88
Self-concept of reading: Perception of difficulty	-0.09	0.95	-1.88	2.77
Meta-cognition: summarising	-0.15	0.96	-1.72	1.36
Meta-cognition: understanding remembering	-0.07	0.95	-1.64	1.50
Meta-cognition: assess credibility	-0.24	0.96	-1.41	1.33
Sense of belonging to school	-0.14	1.02	-3.25	2.75
Disciplinary climate	-0.07	0.95	-2.71	2.03
Perception of competitiveness at school	0.34	1.09	-1.98	2.03
Perception of cooperation at school	-0.01	1.15	-2.14	1.67
Attitude towards school: learning activities	-0.11	1.06	-2.53	1.08
Teacher support	0.21	0.93	-2.74	1.34
Teacher feedback	0.02	1.01	-1.63	2.01
Teacher directed instruction	0.22	1.00	-2.94	1.82
Teacher enthusiasm	-0.09	1.08	-2.21	1.82
Adaptive instruction	0.06	0.97	-2.26	2.00
Teachers' stimulation of reading engagement	0.07	1.01	-2.30	2.08
PISA Reading achievement	464.82	84.22	210.67	725.22
School level variables (N= 186)				
Mean SES	-1.19	0.75	-3.55	1.10

HLM Analysis Results

In order to answer the research question, two HLM models were used in the study. The HLM analysis results are provided in Table 3. First, the random effects model (null model) provided the total variance of reading performance between and within schools. Overall, mean score for reading literacy was 459.93 with 4.96 standard error. The Intra Class Correlation (ICC) value represents the proportion of variance in reading performance across schools and was calculated. The ICC value was .61, which indicated that 61% of the variance was explained in overall reading performance among schools in Turkey.

In Model 1, results showed that non-cognitive variables significantly related to reading performance after controlling student ESCS and school ESCS except some of the variables related to school climate (perception of competitiveness and cooperation at school), and sense of belonging to school. Meta-cognition indices had a much stronger relationship with reading performance than other student non-cognitive variables (assess credibility, β = 11.64, p <.05; summarising, β = 7.14, p <.05). As shown in Model 2, teacher-related variables were found to be significantly related to reading performance except the variable of teacher enthusiasm. Adaptive instruction was the largest predictor (β = 5.35, p <.05) on reading performance with an increase in one unit associated with about 5 points increase in score. Finally, full model including all student and teacher-related factors showed that ESCS, all motivational variables (competitiveness, mastery of goal orientation, work mastery, and fear of failure), self-belief variables, learning strategies (meta-cognition), and affect variable (reading enjoyment) showed a significant relationship with reading performance at the student level. Meta-cognition indices had the strongest predictors of reading achievement (assess credibility, β = 11.29, p <.05; summarising, β = 7.13, p <.05; understanding and remembering, β = 6.04, p <.05), followed by self-concept of reading. Perception of competence was positively related with reading performance (β = 5.96, p <.05) but perception of difficulty was negatively related (β = -6.34, p <.05). In addition, only disciplinary climate had a positive relationship with reading performance. Overall, the fixed effects of student non-cognitive variables were almost the same after controlling all teacher-related and school-related variables. Besides, most of the teacher-related factors were statistically significant in relation to reading performance after controlling student non-cognitive variables and school variables in the full model. The teachers' adaptive instruction (β = 3.87, p <.05) and teachers' directed instruction (β =-3.60, p <.05) had a higher association than the other teacher-related variables on reading performance. When considering the direction of relationship, teacher-directed instruction, teacher feedback, and teacher enthusiasm were negatively related with on average with reading literacy. Mean ESCS as a school level variable also showed a significant relationship with reading literacy.

Table 3. HLM analysis results for reading performance

	Null Model Coefficent (*β*) (*SE*)	Model 1: Student only	Model 2: Teacher only	Model 3: Full model Coefficent (*β*) (*SE*)
Intercept, γ00	459.93 (4.96)***	466.25 (2.94)***	461.10 (3.54) ***	464.82 (2.90) ***
Student level				
Student background				
ESCS		3.25 (0.71)***	4.65 (0.75)***	3.57 (0.70) ***
Student non-cognitive factors				
Reading Enjoyment		4.04 (0.84)***		4.01 (0.83)***
Motivation to master tasks		-3.00 (0.79)***		-2.98 (0.80)***
Fear of failure		1.74 (0.64)**		1.62 (0.66)*
Mastery of Goal Orientation		-4.57 (0.70)***		-4.39 (0.72)***
Competitiveness		3.73 (0.68)***		3.76 (0.67) ***
Self efficacy		2.29 (0.72)**		2.09 (0.74)**
Self-concept of reading: perception of competence		5.63 (0.81)***		5.96 (0.82)***
Self-concept of reading: Perception of difficulty		-6.24 (0.74)***		-6.34 (0.75)***
Meta-cognition: summarising		7.14 (0.82)***		7.13 (0.79) ***
Meta-cognition: understanding remembering		6.23 (0.77)***		6.04 (0.79) ***
Meta-cognition: assess credibility		11.64 (0.82)***		11.29 (0.79) ***
Sense of belonging to school		0.03 (0.63)		0.16 (0.65)
Disciplinary climate		3.13 (0.81)***		3.27 (0.80) ***
Perception of competitiveness at school		0.05 (0.67)		0.33 (0.68)
Perception of cooperation at school		-0.73 (0.63)		-0.60 (0.62)
Attitude towards school: learning activities		1.45 (0.71)*		1.40 (0.72)
Teacher related factors				
Teacher support			2.87 (0.79)***	2.26 (0.80)**
Teacher feedback			-3.91 (0.79)***	-2.80 (0.83)***
Teacher-directed instruction			-3.76 (0.85)***	-3.60 (0.89)***
Teacher enthusiasm			0.18 (0.79)	-2.23 (0.78)**
Adaptive instruction			5.35 (0.93)***	3.87 (0.94)***
Teachers' stimulation of reading engagement			2.91 (0.92)**	1.59 (1.01)

School level			
School Mean ESCS	49.94 (4.23)***	55.50 (4.98)***	49.33 (4.16)***
Explained variance by the model			
Within-school variability (%)	0.21	0.03	0.22
Between-school variability (%)	0.65	0.49	0.67

p<.05, **p<.01, *** p<.001

The proportion of variances explained by each model is also provided in Table 3. The following formula was used to calculate the proportion of variance at level 1 and level 2 in HLM (Luo & Azen, 2013):

$$R^2 = 1 - \frac{\theta}{\theta_{null}}$$

θ represents the variance component in the level 1 or level 2, and θ null represents the model without predictors. In Model 1, 21% of the student level variation was explained by the inclusion of student non-cognitive variables, whereas 65% of the school level variance was explained by the inclusion of school mean ESCS. In Model 2, student-level variables related to teacher behaviors explained only 3% of the student-level reading literacy score variance, and school-level variance (school mean ESCS) explained 49% of the school-level reading literacy score variance. Lastly, all of the variables at both levels were included in Model 3. The amount of variance in mean reading literacy for Turkey within schools and across schools was 22% and 67%, respectively. The explained variance has been increased when all student, teacher-related, and school-related variables are included as a full model when compared to the explained variances in Model 1 and Model 2.

Discussion

Through HLM analysis, this study was aimed to investigate to identify the most important non-cognitive factors on reading performances of Turkish students in PISA 2018. The study proposed an explanatory model to predict some of the non-cognitive of student-related and teacher-related factors on reading performance. ESCS as a background variable was considered an effective predictor of student and school reading achievement. The finding, in line with previous studies (Dinçer & Uysal, 2010; Ersan & Rodriguez, 2020; Smiths & Gündüz Hoşgör, 2006; Tabak & Çalık, 2020), showed that ESCS was a prominent factor explaining student achievement. The results revealed that most of the non-cognitive measures in PISA 2018 have a significant relationship with student reading performance. Meta-cognitive strategies in special meta-cognition: assessing credibility were the best predictors of reading performance at student level in PISA. The finding was consistent with previous studies regarding PISA 2018 using different groups and methods (Depren & Depren, 2021; Gamazo & Martinez-Abad, 2020). Depren & Depren (2021) focused on the high levels of students in PISA 2018 for Turkey and China by using the activity region finder algorithm method. Meta-cognition competencies specifically meta-cognition: assess credibility was the only factor that maximize the student achievement among other variables both Turkey and China. The findings generally showed that students in Turkey were well aware of meta-cognitive strategies and able to use them efficiently. The students who use higher level of these strategies are more successful in reading literacy. Several studies also showed that students' use of meta-cognitive learning strategies contributes to developing their reading literacy (Carrell et al., 1998; Şen, 2009; Qi, 2021). Thus, it is important to develop students' meta-cognitive capabilities as twenty-first century skills. In the group of self-beliefs construct, variables of self-concept, including perception of ability and perception of difficulty, were the best predictors of individual-level student achievement in reading literacy. Academic self-concept has also been highlighted by previous studies (Chapman et al., 2000; Ma et al., 2021). The other influential non-cognitive factors in the model were reading enjoyment as an affect variable, mastery of goal orientation among motivational variables, and disciplinary climate in the school climate construct. Academic emotions in different subjects, like reading enjoyment, play an important role in students' cognitive processes, their decisions, motivation, and achievement (Pekrun, 2006; Pekrun et al., 2017; Goetz et al., 2008). Student achievement is also associated with mastery-approach goals. Students adopting mastery goals are more likely to gain an increase in understanding, development, and success even when they face difficulties. (Ames & Archer, 1988). The present study showed a negative relationship between students' goal-oriented attitudes and their reading performance. The OECD reported that 21 countries, including Turkey, had more than 5% of students who had an immigrant background. PISA 2018 results showed that immigrant students in many countries tend to show low performance and have surprisingly more goal-oriented attitudes than non-immigrant students (OECD, 2019c, p.201). Reports of immigrant students who had more goal-oriented attitudes than non-immigrant students may explain the negative relationship between mastery goal orientation and reading performance in the study. Lastly, the disciplinary climate in a school was a significant predictor of reading performance. Students who reported being in a positive school environment had higher performance in reading literacy than students in a negative school environment.

The results showed that most of the teacher-related factors had significant factors even after all student-related factors and background variables were taken into account. Regarding teacher behaviors, teachers' instructional behaviors, such as adaptive instruction, and teacher-directed instruction have much more influence on reading performance than the other teacher-related factors. The results showed that students in Turkey mostly benefit from the teachers' instructional approach. Students who felt supported by their teachers showed higher performance in reading literacy. Several studies also reported that teachers' support was associated with students' higher academic performance (Ma et al., 2021; Ricard & Pelletier, 2016; Yıldırım, 2012; Yıldırım & Yıldırım, 2019). Adaptation of instruction showed a significant relationship with reading literacy. Teachers adjust their instructions in response to student needs. Similarly, research studies show that teachers' ability to adapt instruction is likely to increase student achievement (Gambrell et al., 2011; Kalkan et al., 2020). While teacher support and teacher adaptive instruction are positively associated with reading performance, other teacher-related behaviors, such as teacher-directed instruction, teacher feedback, and teacher enthusiasm, were negatively associated with reading performance. The research studies reported that teacher instructional practices (e.g. teacher-directed instruction, teacher feedback) (Boston, 2002; Connor et al., 2004) had a strong impact on low-achieved students. The present study also revealed that low-achieved students had higher scores in reading when their teachers were more enthusiastic in the classrooms. These negative relationships might be explained by the nature of the PISA test design (OECD, 2016 b, p. 68). Teachers' use of different instructional strategies and their different behaviors can help different student groups (i.e., advantaged or disadvantaged students, or advantaged-disadvantaged schools).

Conclusion

The present study showed that student-related and teacher-related non-cognitive variables play crucial roles in students' reading achievement. Most of the student non-cognitive variables were significantly associated with reading performance, especially meta-cognitive strategies, which were the strongest. Teacher-related non-cognitive variables are also significantly related to reading achievement. Teachers' instructional behaviors were the most influential predictors in explaining reading achievement. Overall, fostering these soft skills for both students and teachers in schools is important to increasing student achievement.

Limitations

In the present study, the relationship between some of the non-cognitive factors and reading achievement was investigated with the HLM model by using cross-sectional data. In further research, more student-related, teacher-related, and school-related variables should be included in the multi-level model. In order to understand more about the relationship among non-cognitive variables, multilevel path analysis should be done in further studies. In addition, the present study relied on student self-reported data in the student questionnaire. Despite its some limitations, the results of this study contributed to understanding various student and teacher-related non-cognitive variables and their relationship with student reading achievement. In general, the results suggest that fostering soft skills is important not only for students but also for teachers. Conducting experimental or longitudinal studies to investigate any causal effects about the effectiveness of non-cognitive factors would be important to enlighten in the further studies. Examining and comparing non-cognitive factors across different cultures would also be useful.

Conflicts of Interest

There is no conflict of interest for individuals or institutions in this research.

Ethical Approval

Ethical permission (2022/018) was obtained from Sinop University institution for this research.

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