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Understanding Non-Cognitive Profiles of Students Through Cluster Analysis: A Cross-Country Study Based On Pisa 2022 Data

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Abstract

This study classified students according to non-cognitive variables and PISA 2022 mathematics literacy scores. Using a survey design, data from 221.031 students across 31 countries were analyzed through two-step cluster analysis, which yielded six distinct clusters. Cluster 1 demonstrated the highest mathematics literacy scores but relatively low levels of perseverance, curiosity, cooperation, and empathy. Cluster 2 was characterized by a strong sense of belonging, emotional control, and resilience to stress. Cluster 3 exhibited the lowest sense of belonging and the highest levels of bullying. Cluster 5 reflected high levels of cooperation, empathy, and assertiveness, whereas Cluster 6 was marked by strong perseverance and curiosity despite having the lowest mathematics literacy scores. Cross-country comparisons revealed several notable patterns. Effort and persistence were lowest in Chinese Taipei, Hong Kong, and Macao. Sense of belonging, cooperation, and empathy were strongest in Switzerland, Germany, and Spain, but weakest in Türkiye and Hong Kong. Curiosity was particularly high in Türkiye and Portugal, while stress resistance and emotional control were most evident in Finland and Denmark. Additional variations across countries were also identified.

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Introduction

Formal education systems tend to prioritize students' academic achievement over the development of non-cognitive skills (Guo et al., 2023; Niu, 2024a). However, a growing body of research indicates that academic success is closely associated with students' ability to manage goal-directed behaviors, sustain positive social relationships, and regulate their emotions (Guo et al., 2023). In response to this growing recognition, the Organisation for Economic Co-operation and Development (OECD) has incorporated a wide range of contextual variables into its international assessments, thereby offering an important basis for examining the links between non-cognitive variables and academic performance (OECD, 2024a, 2024b).

Alongside cognitive abilities, non-cognitive variables play a central role in students' academic and psychological development (Eluwa, 2024; Guo et al., 2023; Joswick et al., 2022; Lee & Stankov, 2018; Liu et al., 2023; Miyamoto et al., 2015; Niu, 2024b; Pitlik, 2021; Zell & Lesick, 2022). These variables are also associated with greater psychological resilience and improved mental well-being (Cristóvão et al., 2017; Durlak et al., 2011; Liu et al., 2023; Miyamoto et al., 2015; Niu, 2024b; Wang & King, 2025). Some evidence even suggests that strengthening non-cognitive competencies may be as influential as, or in some cases more influential than, enhancing cognitive skills in supporting academic achievement (Semeraro et al., 2020). Nevertheless, much of the existing literature is based on relatively small samples or geographically limited datasets, which restricts the generalizability of findings and limits cross-national comparisons (Burchinal et al., 2020; Dobbs et al., 2006; Linnakyla & Malin, 2008; McCormick et al., 2021).

Findings regarding the relationship between non-cognitive variables and mathematics performance have been mixed. Dobbs et al. (2006) reported relatively weak associations between non-cognitive variables and mathematics-related literacy. In their study, traits such as initiative, self-control, and attachment showed only limited relationships with mathematical ability among students receiving early mathematics interventions. Similarly, McCormick et al. (2021) found that non-cognitive skills did not have significant effects on mathematics performance. By contrast, Burchinal et al. (2020), using a longitudinal design, showed that non-cognitive skills significantly predicted developmental trajectories in mathematics from kindergarten through third grade. Likewise, Liu et al. (2023) found that task performance and open-mindedness were positively associated with mathematics achievement and reported that task performance, emotional regulation, collaboration, open-mindedness, and engagement with others together explained 1.1% of the variance in mathematics performance. Guo et al. (2023) similarly identified self-control, trust, optimism, and energy as among the most influential non-cognitive skills for both academic and life outcomes, noting that these factors accounted for a substantial proportion of the variance in OECD cognitive test scores, school grades, classroom engagement, and teacher-reported performance. In addition, Zell and Lesick (2022), in a meta-analysis of 54 studies on the Big Five personality traits and academic achievement, found that conscientiousness had a moderate positive association with academic performance, followed by open-mindedness within the OECD framework, whereas the remaining traits showed weak or negligible relationships.

Literature Review

Large-scale assessments are systematic evaluation practices designed to measure student achievement at both national and international levels (Kjærnsli & Lie, 2011; Simon et al., 2013). International large-scale assessments, in particular, seek to compare student performance and learning environments across countries, provide an overview of participating education systems, and support policymakers in identifying national educational challenges and developing evidence-based improvement strategies (Arıkan et al., 2020; Bertling & Alegre, 2019; Clarke & Luna-Bazaldua, 2021; Cresswell et al., 2015; Torney-Purta & Amadeo, 2013).

One of the most comprehensive and widely recognized of these assessments is the Programme for International Student Assessment (PISA). Conducted every three years since 2000 under the auspices of the Organisation for Economic Co-operation and Development (OECD), PISA evaluates how effectively 15-year-old students can apply their knowledge and skills to real-life situations (Cresswell et al., 2015; OECD, 1999; Torney-Purta & Amadeo, 2013). The assessment focuses on three core domains: mathematics, science, and reading literacy (Kjærnsli & Lie, 2011; OECD, 2023a). Beyond cognitive achievement, PISA also gathers extensive background information through student questionnaires designed to capture factors associated with learning and performance. These include a range of non-cognitive variables reflecting students' attitudes, emotions, and learning-related behaviors (Bertling & Alegre, 2019; Kutsyuruba et al., 2015; Lee & Stankov, 2018; Wilson-Fadiji & Reddy, 2023). Building on this framework, the present study aims to classify countries primarily according to these non-cognitive variables and to examine how these profiles are associated with mathematics literacy achievement.

Non-Cognitive Variables

It is increasingly recognized that schools should move beyond teaching academic content alone and also foster non-cognitive skills in order to prepare students for the complexities of a diverse and rapidly changing world. These competencies are essential for students' long-term success both within and beyond the classroom (Mahoney et al., 2018). Moreover, contemporary classrooms are becoming increasingly diverse, including students from minority backgrounds, those with disabilities, and learners with different learning styles. In this context, non-cognitive competencies contribute to the development of safe, supportive, and inclusive learning environments (De Smedt, 2022; Li, 2024).

Skills such as cooperation, resilience, curiosity, perseverance, empathy, emotional control, and assertiveness have been highlighted in PISA studies as important predictors of academic achievement (Bertling & Alegre, 2019). These attributes reflect a combination of personal dispositions and self-regulatory capacities, including emotional states, coping strategies, behavioral regulation, and emotional control. Together with cognitive performance, they constitute essential competencies for success in both school and life (OECD, 2021).

Students' perceptions of these non-cognitive variables are particularly important because negative feelings, such as low curiosity or high stress, may hinder mathematics learning. Emotional responses to mathematics, including anxiety and disengagement, often act as barriers to participation and performance. Given the prevalence of such negative emotions across age groups, the development of positive non-cognitive characteristics has become increasingly important (Jensen, 2024; OECD, 2024). Joswick et al. (2022) argued that integrating non-cognitive skill development into instruction can improve learning experiences by promoting collaboration, strengthening mathematical discourse, reducing negative emotional reactions, enhancing engagement and achievement, and supporting college readiness. Accordingly, examining students' perceptions of non-cognitive variables across countries and their relationship with mathematics literacy constitutes an important focus of this study.

Among these variables, curiosity, perseverance, and self-confidence appear to have particularly meaningful associations with academic achievement. Lee and Stankov (2018) showed that although these relationships are modest in magnitude, they are statistically significant. Students with stronger task performance skills, especially persistence, and higher curiosity tend to earn better grades in reading, mathematics, and the arts, and are less likely to arrive late or skip school (OECD, 2024a). Curiosity promotes self-directed learning (Duckworth et al., 2007; Hattie, 2023; OECD, 2024a) and supports open-mindedness, thereby facilitating engagement in tasks requiring flexible and innovative thinking (Singh & Manjaly, 2022). However, Schoenherr et al. (2025) found that although positive activating emotions such as curiosity were positively associated with mathematics achievement, the effect of curiosity itself was not statistically significant. Perseverance, by contrast, reflects the determination to overcome challenges, sustain effort, develop strategies, and persist despite obstacles (DiNapoli, 2023; Guo et al., 2023). Persistent students tend to interpret challenges as opportunities for growth and display resilience and analytical thinking (Duckworth et al., 2007; Guo et al., 2023; Yang & Ogata, 2023). Likewise, Xiao and Sun (2021) found that highly motivated and less anxious students are more likely to persist when facing difficulties. Although Roberts, Caspi, and Moffitt (2003) reported only weak but significant links between non-cognitive traits and academic performance, findings from PISA 2022 showed that students with higher levels of curiosity and persistence scored, on average, approximately 11 points higher in mathematics than their peers across more than 50 countries and economies (OECD, 2023a). Given that mathematics requires sustained effort, iterative reasoning, and persistence in problem solving, perseverance appears to play a particularly important role in mathematics literacy.

As education systems continue to recover from the disruptions caused by the COVID-19 pandemic, prolonged school closures and reduced peer interaction have made students' adjustment to changing learning contexts more difficult. Evidence suggests that students who experience lower stress and use effective coping strategies tend to perform better academically (Gustems-Carnicer, Calderón, & Calderón-Garrido, 2019). Competencies such as emotional regulation, stress tolerance, and collaboration support students in managing setbacks and maintaining engagement (Jensen, 2024; OECD, 2024). In the post-pandemic context, these characteristics may be as important as, or even more important than, cognitive skills for successful learning and adaptation (OECD, 2024a). In particular, emotional regulation and autonomy have become increasingly critical for sustaining persistence and attention in hybrid and online learning environments.

Previous research has also shown that collaboration is closely linked to empathy and may substantially reduce bullying behaviors in educational settings (Van Ryzin & Roseth, 2019). This suggests that collaboration not only supports academic learning but also contributes to a more empathetic and supportive classroom climate, which may, in turn, enhance mathematics literacy. However, empirical agreement regarding the direct relationship between stress management and academic achievement remains limited (OECD, 2021). The influence of emotional regulation and stress resilience on mathematics performance appears to vary depending on contextual and individual factors. One possible explanation for this inconsistency is that most education systems do not address non-cognitive skills as systematically as cognitive competencies. This study therefore seeks to contribute to the literature by examining these variables alongside mathematics literacy across different national contexts.

Positive and negative emotions associated with school life, such as sense of belonging, perceived safety, and experiences of bullying, also play a decisive role in shaping student-student and student-teacher relationships, both of which are important predictors of mathematics literacy (Bertling & Alegre, 2019; Kutsyuruba, Klinger, & Hussain, 2015). Educational environments characterized by inclusion, emotional safety, and mutual respect tend to yield more favorable academic and social outcomes than those marked by exclusion or hostility. School climate strongly influences students' motivation, engagement, and achievement (Loukas, 2007). Bullying, as one of the most harmful indicators of a negative school climate, can undermine emotional regulation, trust, and academic success (Huang, 2022; Winnaar, Arends, & Beku, 2018). Still, findings remain mixed, as some studies have reported only weak or negligible relationships (Hanish & Guerra, 2002; Nakamoto & Schwartz, 2010). In contrast, a strong sense of belonging has been associated with greater emotional and academic competence, as well as improved collaboration and peer communication (OECD, 2023a; Huang, 2022). Examining these dynamics can provide valuable insights for policymakers seeking to improve students' well-being, sense of belonging, and mathematics literacy across educational systems.

Beyond its traditional applications in biology, cluster analysis has become an important analytical tool in educational research for identifying student typologies based on achievement (Eser & Çobanoğlu-Aktan, 2021; Gamazo & Martinez-Abad, 2020; Hope, Chavous, Jagers, & Sellers, 2013; Kıray et al., 2015; Mansur & Yusof, 2018; Singh, Nagar, & Sant, 2016), examining teaching quality (Acquah, Tandon, & Lempinen, 2016), and evaluating teacher education processes (White & Bembenutty, 2013). More recently, cluster analysis has also been used to explore classroom learning environments (Amuah et al., 2025; den Brok et al., 2011). For example, Amuah et al. (2025) identified two clusters reflecting positive and negative perceptions of mathematics classroom environments, whereas den Brok et al. (2011) identified six classroom environment profiles across countries and reported that Turkish classrooms were often characterized by limited teacher support and strong task orientation.

Similarly, a number of studies have employed clustering techniques to analyze variables included in PISA (Akın & Eren, 2012; Aksu, Güzeller, & Eser, 2017; Kjærnsli & Lie, 2011; Otbiçer-Acar, 2012). While some used hierarchical clustering methods (Akın & Eren, 2012; Aksu, Güzeller, & Eser, 2017; Kjærnsli & Lie, 2011; Linnakyla & Malin, 2008), others preferred non-hierarchical k-means clustering (Otbiçer-Acar, 2012; Aksu, Güzeller, & Eser, 2017;

Amuah et al., 2025). A smaller number of studies have applied two-step clustering to improve classification accuracy (Akın & Eren, 2012). For example, Otbiçer-Acar (2012) examined Türkiye's position among OECD and candidate countries using PISA 2009 data and located Türkiye in a cluster with Bulgaria, Chile, Colombia, Dubai, Israel, Jordan, Mexico, Romania, Serbia, Thailand, Trinidad and Tobago, and Uruguay. Likewise, Aksu, Güzeller, and Eser (2017) clustered 43 participating countries in PISA 2012 according to mean scores on self-efficacy, interest, and attitude measures. However, despite the widespread use of clustering methods, no previous study appears to have classified countries within the PISA framework using two-step clustering based specifically on non-cognitive variables such as sense of belonging (BELONG), perseverance (PERSEVAGR), curiosity (CURIOAGR), cooperation (COOPAGR), empathy (EMPATAGR), assertiveness (ASSERAGR), stress resistance (STRESSAGR), emotional control (EMOCOAGR), effort in mathematics (MATHPERS), and bullying experiences (BULLIED). This gap highlights the importance of examining how these variables collectively shape mathematics literacy across different national contexts.

Finally, the effects of these competencies may vary substantially across countries due to cultural and educational differences (Miyamoto et al., 2015). Certain skills may be more relevant or more effective in some contexts than in others. For instance, Niu et al. (2025) found that curiosity significantly predicted mathematics performance in Korea, Finland, and Denmark, but not in Singapore. In the same study, motivation emerged as a strong predictor of mathematics achievement in Finland, whereas it was not significantly associated with performance in Singapore, Korea, or Denmark. Similarly, Niu (2025) reported that task performance had the strongest influence on academic achievement across China, Indonesia, Finland, Ukraine, Colombia, and Brazil, while emotional regulation and interpersonal engagement had moderate effects, and collaboration and open-mindedness showed weaker relationships. These findings underline the need for further cross-national research examining how non-cognitive variables interact with mathematics literacy across different educational systems.

The Aim of the Study

The aim of this study was to classify students based on non-cognitive variables derived from the PISA background questionnaires. Specifically, the study examined students' country of origin, PISA mathematics literacy scores, sense of belonging at school, experiences of bullying, perseverance, curiosity, cooperation, empathy, emotional control, assertiveness, stress resistance, and persistence in mathematics. In line with this aim, the study addressed the following research question:

How are students classified according to these non-cognitive variables using two-step cluster analysis?

Method

This study employed a survey research design, a descriptive approach commonly used to collect data on the opinions, attitudes, behaviors, or characteristics of individuals, groups, or phenomena within a defined population (Fraenkel & Wallen, 2009). Drawing on non-cognitive variables obtained from the PISA background questionnaires together with students' mathematics literacy scores, the study aimed to describe and compare student profiles across countries, with particular emphasis on the non-cognitive constructs assessed in PISA (Creswell, 2012).

Population and Sample

In 2022, approximately 700.000 students from 81 OECD member and partner economies, representing nearly 29 million students worldwide, participated in PISA (OECD, 2023a). Of these, 37 were OECD member countries. The present study was conducted with a final sample of 221.031 students who had complete data for all selected variables. The distribution of students by country, together with their mathematics literacy scores, is presented in Table 1.

In terms of sample size, Spain contributed the largest proportion of participants (f = 27.779, 12.6%), followed by Canada (f = 17.698, 8.0%) and Australia (f = 12.204, 5.5%). By contrast, the smallest samples were obtained from Malta (f = 2.623, 1.2%) and Iceland (f = 2.731, 1.2%).

Regarding mathematics literacy, Singapore had the highest mean PVMATH score (M = 576.87, SD = 98.09),

Table 1: Distribution of Students according to Country and Mathematics Literacy Scores

			PVMATH					PVMATH	
Country	f	%	M	SD	Country	f	%	M	SD
Australia	12204	5.5	494.16	92.48	Ireland	5339	2.4	495.23	74.65
Canada	17698	8.0	497.60	86.08	Iceland	2731	1.2	472.57	79.54
Switzerland	5765	2.6	518.74	87.94	Italy	9751	4.4	479.80	81.76
Chile	5092	2.3	439.23	74.15	Korea	6139	2.8	535.15	99.83
Czech Republic	7645	3.5	506.91	89.93	Lithuania	6461	2.9	479.21	81.23
Germany	4921	2.2	492.19	87.01	Macao (China)	4275	1.9	553.08	88.61
Denmark	5266	2.4	486.95	78.44	Malta	2623	1.2	480.77	89.65
Spain	27779	12.6	488.17	77.95	Netherlands	4397	2.0	506.67	97.45
Estonia	6008	2.7	516.61	79.06	New Zealand	4022	1.8	490.96	91.33
Finland	8585	3.9	488.33	84.14	Poland	5266	2.4	504.60	80.03
France	5601	2.5	484.96	84.70	Portugal	6270	2.8	481.35	82.01
United Kingdom	10216	4.6	491.05	90.13	Romania	6308	2.9	450.48	87.74
Greece	5722	2.6	441.43	76.10	Singapore	6352	2.9	576.87	98.09
Hong Kong (China)	5276	2.4	552.10	98.09	Chinese Taipei	5521	2.5	539.21	105.96
Croatia	5482	2.5	470.37	81.46	Türkiye	6683	3.0	457.38	85.08
Hungary	5633	2.5	486.65	85.83					
Total						221.031	100		

followed by Macao (China) (M = 553.08, SD = 88.61) and Hong Kong (China) (M = 552.10, SD = 98.09). In contrast, Chile (M = 439.23, SD = 74.15), Greece (M = 441.43, SD = 76.10), and Romania (M = 450.48, SD = 87.74) showed the lowest mean mathematics literacy scores. Türkiye had a mean mathematics literacy score of 457.38 (SD = 85.08), which was below the overall performance levels observed in many participating countries.

Overall, the descriptive findings indicate substantial cross-national variation in both sample representation and mathematics literacy performance, providing a suitable basis for subsequent clustering analyses.

2.2. Data Collection

Data for this study were drawn from the student-level background questionnaires and mathematics literacy test scores included in the PISA 2022 dataset. In the PISA 2022 administration, students completed the background questionnaires following the cognitive assessment sessions. The dataset used in this study was retrieved from the official PISA website (www.pisa.oecd.org). Because the data are publicly available, no special authorization was required for their use. The questionnaire data were reported at the construct level rather than at the individual item level.

The non-cognitive variables examined in this study served as independent variables and were measured on an interval scale as standardized indices generated by PISA. The cluster analysis included mathematics literacy score (PVMATH), country (CNT), sense of belonging at school (BELONG), exposure to bullying (BULLIED), curiosity (CURIOAGR), assertiveness (ASSERAGR), effort and perseverance in mathematics (MATHPERS), cooperation (COOPAGR), stress resistance (STRESSAGR), perseverance (PERSEVAGR), emotional control (EMOCOAGR), and empathy (EMPATAGR), yielding a total of 11 variables. Among these, all variables except country (CNT) were continuous.

Data Analysis

Cluster analysis was employed to identify patterns and classify students according to the selected non-cognitive variables. Classification is considered a fundamental human cognitive activity (Aldenderfer & Blashfield, 1984). Cluster analysis is a statistical technique used to identify natural groupings within a dataset based on observed similarities among cases (Tkaczynski et al., 2010). More specifically, it organizes observations into relatively homogeneous groups while maximizing differences between groups (Campens et al., 2024; Everitt et al., 2011; Kohonen, 2014; Mansur & Yusof, 2018; Nisbet, Elder, & Miner, 2009; Pratama & Husnayaini, 2022; Singh et al., 2016). It does not rely on parametric assumptions such as normality, linearity, or homogeneity, nor does it require traditional significance testing (Chiang, 2021; Everitt et al., 2011). This flexibility makes it an appropriate method for identifying meaningful groupings within large and complex educational datasets such as PISA.

In this study, two-step cluster analysis was preferred because it can handle both categorical and continuous variables and is especially effective for large datasets (Campens et al., 2024). Another advantage of this method is its ability to automatically determine the optimal number of clusters. However, because it excludes cases with missing data, only participants with complete data were included in the analysis. The procedure consists of two main stages: pre-clustering and clustering (Campens et al., 2024; Tkaczynski et al., 2010; Zhang et al., 1997). In the first stage, observations are grouped into small sub-clusters. In the second stage, these sub-clusters are merged using a hierarchical clustering approach based on a distance criterion. When categorical variables are included, the log-likelihood distance measure is applied. The optimal number of clusters is determined using the Schwarz Bayesian Information Criterion (BIC) and the ratio of distances between clusters (Campens et al., 2024; Tkaczynski et al., 2010). In addition, the Silhouette index was used to

Table 2: *Analysis of Variance for Variables Included in the Clustering Analysis*

Variables		SS	df	MS	F*
Sense of belonging (WLE)	Between Groups	19862.21	5	3972.44	4876.01
	Within Groups	168208.50	206469	.82	
	Total	188070.70	206474		
Being bullied (WLE)	Between Groups	2975.63	5	595.13	628.94
	Within Groups	195367.48	206469	.95	
	Total	198343.11	206474		
Perseverance (WLE)	Between Groups	39931.57	5	7986.32	10847.55
	Within Groups	152009.13	206469	.74	
	Total	191940.70	206474		
Curiosity (WLE)	Between Groups	36434.08	5	7286.82	9591.91
	Within Groups	156851.05	206469	.76	
	Total	193285.12	206474		
Cooperation (WLE)	Between Groups	34448.89	5	6889.78	8990.19
	Within Groups	158230.91	206469	.77	
	Total	192679.79	206474		
Empathy (WLE)	Between Groups	26658.90	5	5331.78	6495.75
	Within Groups	169471.81	206469	.82	
	Total	196130.70	206474		
Variables	SS	df	MS	F*	Variables

Variables		SS	df	MS	F*
Assertiveness (WLE)	Between Groups	18275.56	5	3655.11	4099.02
	Within Groups	184109.03	206469	.89	
	Total	202384.58	206474		
Stress resistance (WLE)	Between Groups	7980.18	5	1596.04	1738.61
	Within Groups	189537.74	206469	.92	
	Total	197517.92	206474		
Emotional control (WLE)	Between Groups	10870.15	5	2174.03	2395.80
	Within Groups	187357.09	206469	.91	
	Total	198227.24	206474		
Effort and Persistence in Mathematics (WLE)	Between Groups	15538.27	5	3107.65	3646.56
	Within Groups	175956.06	206469	.85	
	Total	191494.34	206474		
PVMATH	Between Groups	76599476.86	5	15319895.37	1982.25
	Within Groups	1595703990.04	206469	7728.54	
	Total	1672303466.91	206474		

*p<.000

evaluate model quality. Silhouette values range from -1 to +1 with values below 0.30 indicating poor quality and values above 0.50 indicating good fit (Campens et al., 2024).

In PISA, students' mathematics literacy is represented by ten plausible values (PV1-PV10) (Wu & Adams, 2002). In this study, the mathematics literacy variable (PVMATH) was calculated as the mean of these ten plausible values (Brown & Micklewright, 2004). Prior to analysis, the dataset was screened for missing values and outliers, and these cases were removed to ensure data quality. The final analysis was conducted on 221.031 complete observations using IBM SPSS Statistics 25.0.

Findings

This section presents the findings derived from the cluster analysis conducted on the non-cognitive variables. The results of the analysis of variance (ANOVA), which was performed to determine whether the variables included in the model significantly contributed to the clustering process, are presented in Table 2.

As shown in Table 2, all variables included in the cluster analysis had a statistically significant effect on cluster formation ($p < .001$). This finding indicated that the clusters generated based on these variables differed from one another at a statistically significant level.

According to the results of the two-step cluster analysis, Cluster 1 comprised 37.922 students, representing 18.4% of the total sample. Students in this cluster had an average mathematics literacy score of 528.81. Cluster 2 included 50.654 students, accounting for 24.5% of the total sample, with an average mathematics literacy score of 482.95. Cluster 3 contained 25.818 students, corresponding to 12.5% of the total sample, with an average mathematics literacy score of 494.32. Cluster 4 comprised 21.337 students, representing 10.3% of the total sample. Cluster 5 comprised 30.342 students, representing 14.7% of the total sample. Students in this cluster had an average mathematics literacy score of 499.75. Cluster 6 comprised 40.402 students, representing 19.6% of the total sample. Students in this cluster had an average mathematics literacy score of 475.76. However, students in cluster 4 are not from a specific country and were excluded from the analysis because they contain different numbers of students from all countries. For instance, 183 Hong Kong students in cluster 1; 662 Danish students from

Cluster 2; 320 UK students from Cluster 3; 284 Swiss students from Cluster 5 and 361 Hungarian students from Cluster 6 were actually clustered in Cluster 4. These indicate poor clustering performance with Silhouette values lower than 0.30 are interpreted as a poor quality of the model as stated by (Campens et al., 2024). Additionally, 14.556 students were excluded from the analysis due to nonconformity with cluster characteristics. The distribution of countries according to the variables included in the cluster analysis is presented in Table 3, along with the cluster centers for each variable to further illustrate the characteristics and distinctions among the clusters.

As shown in Table 3, the sense of belonging (BELONG) index was highest in Cluster 2 (M = 0.05) and lowest in Cluster 3 (*M* = -0.31). The mean score for being bullied (BULLIED) was lowest in Cluster 1 (*M* = -0.41) and highest in Cluster 3 (*M* = -0.10). Perseverance (PERSEVAGR) was greatest in Cluster 6 (*M* = -0.11) and lowest in Cluster 1 (*M* = -0.25). The curiosity (CURIOAGR) index was also highest in Cluster 6 (*M* = 0.03) and lowest in Cluster 1 (*M* = -0.24). Average scores for cooperation (COOPAGR) followed a similar pattern, being lowest in Cluster 1 (*M* = -0.26), highest in Cluster 5 (*M* = 0.04). The empathy (EMPATAGR) index reached its highest level in Cluster 5 (*M* = 0.02) and its lowest in Cluster 1 (*M* = -0.16). Assertiveness (ASSERAGR) was highest in Cluster 5 (*M* = 0.02) and lowest in Cluster 2 (*M* = -0.18).

The mean score for stress resistance (STRESSAGR) was highest in Cluster 2 (*M* = - 0.41) and lowest in Cluster 3 (*M* = -0.31). Similarly, emotional control (EMOCOAGR) was highest in Cluster 2 (*M* = 0.01) and lowest in Cluster 3 (*M* = -0.20). Effort and perseverance in mathematics (MATHPERS) were highest in Cluster 3 (*M* = 0.10), lowest in Cluster 1 (*M* = -0.22).

Finally, the mathematics literacy score was highest in Cluster 1 (*M* = 528.81) and lowest in Cluster 6 (*M* = 475.76). Based on these findings, it was concluded that countries were grouped into five distinct clusters according to their students' profiles, as summarized in Table 4.

According to Table 4, a total of 31 countries with complete data on non-cognitive variables were included in the clustering analysis. Cluster 3 contained the fewest countries, while Cluster 2 included the largest and most populated group of countries. Figure 1 illustrates the distribution of countries across their relative positions based on the non-cognitive variables.

Table 3. Cluster Centers

	Cluster 1		Cluster 2		Cluster 3		Cluster 5		Cluster 6	
	M	SD	M	SD	M	SD	M	SD	M	SD
BELONG	-.24	.74	**.05**	.93	**-.31**	.81	-.02	.88	-.16	.83
BULLIED	**-.41**	.95	-.37	.94	**-.10**	1.07	-.30	.96	-.25	1.01
PERSEVAGR	**-.25**	.68	-.12	.72	-.21	.86	-.03	.85	**-.11**	.79
CURIOAGR	**-.24**	.77	-.15	.73	-.12	.88	-.05	.86	**.003**	.85
COOPAGR	**-.26**	.68	-.10	.71	-.24	.75	**.04**	.88	-.15	.73
EMPATAGR	**-.16**	.78	-.05	.79	-.08	.90	**.02**	.93	-.06	.83
ASSERAGR	-.12	.73	**-.18**	.69	-.10	1.04	**.02**	.77	-.06	.76
STRESAGR	-.047	.78	**-.041**	.79	**-.31**	1.12	-.05	.96	-.09	.87
EMOCOAGR	-.04	.83	**.01**	.77	**-.20**	1.12	-.04	.89	-.08	.86
MATHPERS	**-.22**	.91	-.11	.83	**.10**	.92	-.10	.91	-.12	.95
PVMATH	528.81	96.04	482.95	79.50	494.32	86.81	499.75	85.08	475.76	91.78

Table 4. *Clusters and Related Countries according to Non-Cognitive Variables*

Cluster Number	Number of Countries in Clusters	Countries
Cluster 1	8	Chinese Taipei, Hong Kong (China), Singapore, Macao (China), Estonia, Netherlands, Lithuania, Poland
Cluster 2	8	Denmark, Spain, Finland, Croatia, Iceland, Italy, Malta, New Zealand
Cluster 3	2	Canada, United Kingdom
Cluster 5	6	Czech Republic, Switzerland, Germany, France, Ireland, Portugal
Cluster 6	7	Australia, Chile, Greece, Hungary, Korea, Romania, Türkiye

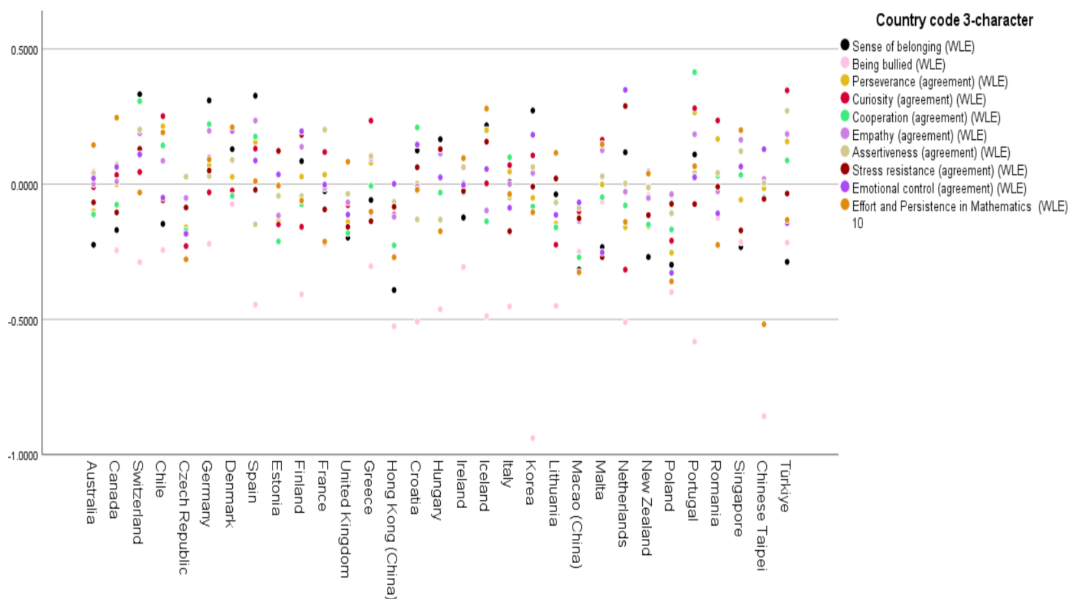

Figure 1. The Relative Positions of Countries According to Non-Cognitive Variables

The cross-country comparison revealed substantial variation in students' non-cognitive profiles, as illustrated in Figure 1. Iceland, Singapore, and Canada reported the highest levels of effort and persistence in mathematics, whereas Chinese Taipei showed notably low levels in this domain. A similar pattern was observed in Poland, Hong Kong (China) and Macao (China), where students demonstrated high mathematics literacy despite relatively low effort and persistence in mathematics. By contrast, students in Türkiye reported greater effort in mathematics than their peers in these East Asian economies, despite achieving comparatively lower mathematics literacy scores. Romania also displayed low levels of effort and persistence, consistent with its relatively low mathematics performance.

With regard to sense of belonging, students in Switzerland, Germany, and Spain reported the highest levels, , which were classified within the second cluster, whereas those in Türkiye, Hong Kong (China), and Macao (China) reported the lowest. Bullying was least prevalent in Korea, Chinese Taipei, and Portugal, but most frequently reported in Australia, followed by New Zealand and Malta. Curiosity was highest in Türkiye, Chile, and Portugal, and lowest in the Netherlands, Lithuania, and the Czech Republic.

Regarding perseverance, students in Chile, Iceland, and Portugal reported the highest levels, whereas those in Poland, New Zealand, and the Netherlands reported the lowest. Assertiveness was more pronounced in Türkiye, Switzerland, and France, while lower levels were observed in Spain, Croatia, and Hungary. Similarly, cooperation was strongest in Switzerland, Germany, and Portugal, but weakest in Hong Kong (China), Macao (China), and Estonia. Empathy followed a similar pattern, with the highest levels in Switzerland, Germany, and Spain and the lowest in Hong Kong (China), Macao (China), Estonia, and Lithuania.

Finally, stress resistance was highest in the Netherlands, Denmark, and Finland and lowest in Malta, Italy, and Singapore. A comparable trend emerged for emotional control, which was strongest in the Netherlands, Denmark, and Finland and weakest in Malta, Poland, and the Czech Republic.

Discussion

In this study, 31 countries with complete data on the selected non-cognitive variables were included in the cluster analysis. The findings revealed distinct cross-country patterns. Cluster 1, consisting of Chinese Taipei, Hong Kong (China), Singapore, Macao (China), Estonia, the Netherlands, Lithuania, and Poland, had the highest mathematics literacy scores but comparatively low levels of perseverance, curiosity, cooperation, and empathy. Cluster 2, including Denmark, Spain, Finland, Croatia, Iceland, Italy, Malta, and New Zealand, was characterized by high belonging, emotional control, and stress resilience, indicating a relatively healthy social-emotional profile. Cluster 3, represented by Canada and the United Kingdom, showed the lowest sense of belonging, the highest levels of bullying, and the lowest emotional control. Cluster 5, comprising the Czech Republic, Switzerland, Germany, France, Ireland, and Portugal, demonstrated strong cooperation, empathy, and assertiveness. Cluster 6, including Australia, Chile, Greece, Hungary, Korea, Romania, and Türkiye, exhibited high perseverance and curiosity but the lowest mathematics literacy scores. Overall, these clusters reflected substantial disparities in both non-cognitive characteristics and mathematics literacy across countries.

Although high-performing East Asian systems were grouped in Cluster 1, students in some of these countries, particularly Chinese Taipei, Hong Kong (China), and Macao (China), reported relatively low levels of effort and persistence in mathematics despite strong achievement. This pattern may be explained by cultural interpretations of effort. In Confucian-heritage contexts, effort is often normalized as an expected part of academic life rather than perceived as an exceptional personal quality. As a result, students may underestimate their own effort even when they achieve at high levels. This interpretation contrasts with studies showing that task performance and persistence are generally associated with stronger academic outcomes across cultures (Liu et al., 2023; Niu, 2025). By comparison, students in Türkiye reported higher effort in mathematics despite lower mathematics literacy, suggesting that students' self-perceptions of effort may be shaped by cultural expectations and educational context as much as by actual performance.

The findings also revealed notable differences in students' social-emotional experiences at school. Although cluster analysis showed that Cluster 2 exhibited higher levels of belonging, emotional control, and stress resilience, while Cluster 3 showed the lowest belonging and highest bullying, country-level comparisons revealed notable variation. Countries such as Switzerland, Germany, and Spain showed higher levels of school belonging, whereas Türkiye, Hong Kong (China), and Macao (China) showed lower levels. For instance, 79% of Swiss and 76% of German students reported a strong sense of belonging, both above the OECD average, while only 12% felt lonely or excluded. Conversely, in Türkiye, only 69% of students reported belonging, with higher levels of loneliness and exclusion (OECD, 2023a, 2023b). Türkiye's exam-oriented educational culture, characterized by large classes, rigid curricula, and limited individualized attention which fosters competition rather than community, weakening students' sense of connection. Socioeconomic inequality might have further exacerbated exclusion and reduce school climate quality. Similarly, in Hong Kong, despite previous research identifying a significant link between mathematics literacy and students' sense of belonging (Linnakylä & Malin, 2008), the focus on 'national education' and the avoidance of sensitive topics might have restricted emotional interaction between teachers and students, particularly among those with strong local identities. These formal and cautious relationships might have weakened emotional connections and diminished students' perceived sense of belonging. These differences are important because school belonging has consistently been associated with safer, more supportive learning environments and stronger academic adjustment (Loukas, 2007; OECD, 2023a, 2023b).

Chile, Iceland, and Portugal demonstrated higher perseverance, while Poland, New Zealand, and the Netherlands showed lower levels, reflecting cultural rather than ability-based differences. In Portugal, persistence is culturally valued and reinforced through education. Iceland's emphasis on resilience and Chile's focus on hard work for social mobility similarly promote perseverance. Conversely, Northern and Western European systems prioritize creativity, independence, and well-being over sustained effort. Early student tracking and autonomy might have further reduced the perceived necessity of persistence across subjects. Thus, perseverance, though respected, is less emphasized than in exam-driven systems where effort and endurance are central to achievement.

Curiosity was higher in Türkiye, Chile, and Portugal, whereas lower levels were observed in the Netherlands, Lithuania, and the Czech Republic. Similarly, assertiveness was high in Türkiye, Switzerland, and France but low in Spain, Croatia, and Hungary. Research indicates that curious and assertive students generally achieve better academic outcomes (Hattie, 2023; OECD, 2024a). Assertive learners tend to take initiative, defend their ideas, and assume responsibility, fostering stronger engagement and performance in cognitively demanding subjects such as mathematics (Oladipo, Arigbabu, & Kazeem, 2012). However, despite high curiosity and assertiveness, students in Türkiye and Greece demonstrated relatively low mathematics literacy. In these contexts, rigid, exam-oriented, and teacher-centered systems prioritize memorization over inquiry and exploration (den Brok et al., 2011). Students preparing for high-stakes exams often encounter theoretical instruction that neglects hands-on or real-world applications. As a result, their natural curiosity and motivation to question, explore, and persist may weaken over time. When opportunities for active participation and independent discovery are limited, curiosity and assertiveness diminish, ultimately reducing mathematics literacy achievement.

Bullying is a strong predictor of academic performance (Huang, 2022; Winnaar, Arends, & Beku, 2018). PISA 2022 data indicate that students in high-performing education systems with strong belonging feel safer and experience fewer bullying incidents (OECD, 2023a, 2023b). As bullying increases, mathematics achievement declines. Victims often experience absenteeism, anxiety, and reduced motivation, negatively affecting mathematical literacy. Although Cluster 3 (Canada and the UK) showed the lowest belonging and highest bullying, country-level comparisons revealed variation. Bullying rates were lowest in Korea, Chinese Taipei, and Portugal, and highest in Australia, New Zealand, and Malta. In Korea and Chinese Taipei, cultural norms emphasizing group harmony and respect for authority likely discourage overt aggression. Portugal's adoption of social-emotional learning and anti-bullying initiatives might have fostered safer school environments (Cristóvão et al., 2017). Conversely, in Australia and New Zealand, large, diverse student populations might have heightened peer tension. Moreover, cross-curricular initiatives addressing social awareness (Miyamoto et al., 2015) might have increased students' sensitivity to recognizing and reporting bullying-related behaviors, contributing to higher reported rates.

Cooperation levels were highest in Switzerland, Germany, and Portugal (Cluster 5 countries), and lowest in Hong Kong, Macao (China), and Estonia (Cluster 1 countries). Similarly, empathy scores were higher in Switzerland, Germany, and Spain, but lower in Hong Kong, Macao (China), Estonia, and Lithuania. In countries such as Switzerland and Germany, apprenticeship models combining academic study with workplace training promote teamwork, shared responsibility, and collaborative problem-solving, which enhance cooperation and empathy. These systems also reflect cultural values of reliability and mutual trust. Research indicates that students with collaborative and curious dispositions engage more deeply in learning, regulate emotions effectively, and connect new knowledge to prior understanding (Jensen, 2024; OECD, 2024a). Cooperation not only improves mathematics literacy but also fosters empathy and reduces bullying by promoting positive peer relationships and positive school climates (OECD, 2024a; Van Ryzin & Roseth, 2019). Conversely, lower cooperation and empathy in Hong Kong, Macao (China), Estonia, and Poland may result from highly competitive, exam-oriented systems emphasizing individual achievement. In such settings, collaboration is often undervalued. Liu et al. (2023) found that Chinese students' mathematics learning emphasizes individual, rule-based cognition, with less reliance on emotional or interpersonal engagement, which may explain lower cooperation-related outcomes. Similarly, Niu (2025) noted that heavy workloads limit time for cooperative learning, as group activities may be seen as distractions from exam preparation.

Stress resistance and emotional control were highest in the Netherlands, Denmark, and Finland. While stress resistance low in Malta, Italy, and Singapore; emotional control was low in Poland, Malta, and the Czech Republic. Northern European systems emphasize student well-being, balance, and moderate academic pressure. In Finland, shorter school days, limited homework, and trust-based learning reduce stress, while mental health support and collaborative teaching enhance resilience. Emotional regulation has been shown to improve academic performance, with stronger effects in Finland than in China (Liu et al., 2023; Niu, 2025; Semeraro et al., 2020). Conversely, Singapore's exam-driven system, heavy workloads, and high parental expectations (Wan et al., 2023) might have increased stress and reduced tolerance. Traditional, exam-oriented structures in Italy and Malta might have similarly intensified pressure. In Central and Eastern Europe, particularly Poland and the Czech Republic, emotional openness and limited socio-emotional instruction might have resulted in lower emotional control. In contrast, calm, cooperative classroom environments in Finland, Denmark, and the Netherlands foster stress resilience and support academic achievement (Guo et al., 2023; Wan et al., 2025).

Limitations and Suggestions

This study has several limitations that should be considered when interpreting its findings. As Lee and Junus (2024) noted, results should not be overgeneralized to represent cross-country similarities or differences, as substantial variation may exist within regions. The cross-sectional nature of PISA data also limits causal interpretations. Moreover, non-cognitive variables such as belonging, perseverance, curiosity, cooperation, empathy, assertiveness, stress resistance, emotional control, and effort in mathematics were based on self-reports, which may involve social desirability bias. Future studies should include perspectives from teachers, parents, and peers to strengthen validity.

The findings suggest that exam-oriented education systems that strongly emphasize performance may undermine students' sense of belonging, curiosity, cooperation, empathy, emotional regulation, and stress resilience. Accordingly, curricula should aim to balance academic achievement with well-being by integrating non-cognitive skill development. In contexts such as Türkiye, where students demonstrate relatively high curiosity but lower mathematics literacy, reducing teacher-centered and exam-focused instruction may be particularly important. Learning environments that encourage exploration, risk-taking, and learning from mistakes can help translate curiosity and motivation into improved academic outcomes.

Additionally, education systems like those in Switzerland and Germany, which align instruction with student ability through early academic and vocational tracking illustrate the benefits of aligning instruction with individual ability. Differentiated curricula that match students' strengths and contribute to students' development both in non-cognitive skills and also in mathematics literacy achievement are suggested.

To strengthen persistence, teachers should support perceived competence and task value (Xiao & Sun, 2021) by setting clear goals, scaffolding tasks, and constructive feedback (Li, 2024). Teaching should build students' confidence in mathematics by breaking complex topics into manageable units, supported with structured guidance and technological tools. This gradual progression helps reinforce students' belief in their abilities. Moreover, student-centered approaches such as differentiated instruction, problem-based learning, and collaborative learning are suggested to foster self-competence and academic achievement as stressed by Bara and Xhomara (2020). Connecting mathematical tasks to students' interests and real-life contexts (De Smedt, 2022) is also suggested to increase engagement and persistence.

While some education systems emphasize cooperation, others show lower performance in this domain. Van Ryzin and Roseth (2019) found that collaboration fostered through empathy significantly reduces school bullying. Collaborative learning thus support both mathematical literacy and inclusive, supportive school environments. Since bullying negatively affects academic achievement and long-term well-being, school leaders and teachers should implement preventive measures and provide targeted support for disengaged or disruptive students to promote a positive and safe school climate.

Perseverance is one of the key determinants of academic achievement, enabling students to manage academic demands, prioritize tasks, and maintain effort despite challenges. Students with strong task performance skills consistently complete assignments, prepare effectively, and seek support when needed. Incorporating organizational skill training and resilience-focused methods, such as project-based learning, can strengthen perseverance.

Türkiye indicated higher curiosity scores but lower mathematics literacy scores. It is stated that curiosity promotes critical thinking but is rarely reflected in traditional assessments. Alternative evaluations like group projects or portfolios could better capture this competency. As Liu et al. (2023) noted, both individual (cognitive, motivational, emotional) and contextual (social, environmental) factors shape mathematics performance; hence, future studies should examine environmental influences on social-emotional and academic outcomes.

Consistent with prior research (Durlak et al., 2011; Eluwa, 2024), non-cognitive skills strongly correlate with achievement. Embedding social-emotional learning programs from early education through high school can enhance performance, decision-making, and motivation while reducing risky behaviors. Also, providing extracurricular activities such as sports, arts, volunteering is suggested since they might contribute to building perseverance, teamwork, curiosity, and self-confidence (Cotter et al., 2015).

Although incorporating non-cognitive characteristics into mathematics instruction is valuable, further research is needed on effective implementation. This includes providing professional development for teachers, identifying classroom opportunities to reinforce these skills, and evaluating intervention outcomes (Cristóvão et al., 2017). Educational policymakers should create resources and examples to support the development of non-cognitive skills within mathematics education.

This study examined the non-cognitive variables of belonging (BELONG), perseverance (PERSEVAGR), curiosity (CURIOAGR), cooperation (COOPAGR), empathy (EMPATAGR), assertiveness (ASSERAGR), stress resistance (STRESSAGR), emotional control (EMOCOAGR), effort and perseverance in mathematics (MATHPERS), and bullying (BULLIED). Future research could incorporate additional constructs such as self-control, responsibility, optimism, self-awareness, and creativity to provide a more comprehensive understanding of non-cognitive characteristics and their links to academic outcomes.

Since cluster analysis results are sensitive to the algorithm employed, different methods may yield varying outcomes. Therefore, future studies are encouraged to use multiple clustering algorithms selected according to variable types and dataset size, and to report any discrepancies among the clustering results to enhance the robustness and interpretability of findings.

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