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# More than ability: A multilevel analysis on how non-cognitive factors predict mathematics achievement in the PISA 2022 for Greece

**Stavros Aivaliotis[1] and Anastassios Emvalotis[2]**

[1]Department of Primary Education, University of Ioannina, Greece (ORCID: 0009-0007-2807-9055)
[2]Department of Primary Education, University of Ioannina, Greece (ORCID: 0000-0002-9568-7831)

**Corresponding Author:** Stavros Aivaliotis, steveaiva01@gmail.com

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**Abstract**

Non-cognitive factors explain a substantial part of students' behavior at school and shape an important part of their school performance. The present study examines the extent to which a number of these factors (in particular, anxiety, self-efficacy and attitudes) predict students' achievement in mathematics, using research data from the recent 2022 cycle of the Programme for International Student Assessment for Greece. Capitalizing on the strengths and advantages provided by multilevel (hierarchical linear) modelling for assessments where the data is structured hierarchically, indicators relating to non-cognitive factors were isolated from the assessment, and their relationship with academic performance in mathematics was examined. The analysis conducted shows that most of the non-cognitive factors examined significantly predict students' achievement in mathematics, with self-efficacy in formal and applied mathematics and anxiety playing the largest role in predicting mathematics achievement, even after accounting for sociodemographic variables. Results further indicate that while self-efficacy is the strongest predictor of success, high anxiety acts as a barrier that dampens the positive effects of other motivational factors. Finally, the study highlights the importance of strengthening the integration of non-cognitive factors in the educational process and systems by adopting targeted interventions, prioritizing mastery experiences and training teachers through programs, to enhance student performance.

**Keywords:** Hierarchical linear model; Mathematics achievement; Multilevel analysis; Non-cognitive factors; PISA

## 1. Introduction

Given the increasing presence of technology and sciences in everyday life, there is a vastly growing need to integrate informed citizens, who are not only capable of solving contemporary problems, but also possess scientific and mathematical reasoning as well as computational thinking skills, into modern society and the labor market (Organisation for Economic Co-operation and Development [OECD], 2023a; World Economic Forum, 2023). Understanding the concept and content of mathematics plays a central role in preparing young people to participate in modern society (OECD, 2023a). Mathematics is a crucial tool for young people, as they face a wide range of issues and challenges in different aspects of their lives. Despite strong demand for academic graduates and skills in mathematics, too few students pursue these fields, mainly due to a lack of interest and weak support systems (Mourshed et al., 2013). Various non-cognitive factors influence students' achievement in mathematics and are part of individual characteristics, such as attitudes towards mathematics, self-efficacy, and mathematics anxiety (Lee & Stankov, 2018; Michaelides et al., 2019; Pitsia et al., 2017; Zhang & Bae, 2020). Studies that attempt a thorough investigation of students' achievement through multilevel analyses and include a range of important non-cognitive factors are scarce (Pitsia et al., 2017), with current literature failing to capture the nested nature of educational data and the importance of such factors, especially in the Greek context (Karakolidis et al., 2016), a gap that our research aims to fill.

In PISA 2022, the main area of study and assessment of literacy was mathematics. As defined in the analytical framework created by OECD for PISA 2022:

> Mathematical literacy is an individual's capacity to reason mathematically and to formulate, employ, and interpret mathematics to solve problems in a variety of real-world contexts. It includes concepts, procedures, facts and tools to describe, explain and predict phenomena. It assists individuals to know the role that mathematics plays in the world and to make the well-founded judgements and decisions needed by constructive, engaged and reflective 21st Century citizens (OECD, 2023a, p. 22).

Therefore, it is important to understand the extent to which young people who complete compulsory education are adequately prepared to use mathematics to think about their lives, plan their future and solve important problems (Bredberg, 2020; OECD, 2023a).

In this context, the investigation of factors related to students' achievement in mathematics has been the centre of interest in international large-scale assessments [ILSAs]. International large-scale assessments assess students' performance in specific cognitive fields and provide the framework for interpreting the results, while also collecting additional data at the student, teacher, principal and/or system levels (OECD, 2023a; Rocher & Hastedt, 2020). The Programme for International Student Assessment [PISA] survey is conducted every three years. For each cycle of assessment, reading, mathematics, or science is chosen as the main area and given greater emphasis than the other two subjects (OECD, 2023a). This survey assesses the extent to which 15-year-old students near the end of their compulsory education have acquired the knowledge and skills necessary for participation in modern societies (OECD, 2023a). The survey evaluates not only students' ability to recall and reproduce knowledge, but also their capacity to build upon what they have learned and to apply it effectively in unfamiliar contexts, both inside and outside school (OECD, 2023a). What distinguishes PISA from other surveys is its focus on education policy, its innovative design of student competencies, its relevance to lifelong learning, its consistency and its broad scope (OECD, 2023b). The technical framework of PISA encompasses the design of its tests, questionnaires and other measurement techniques, sampling rules and procedures, and implementation protocols established to ensure fairness and comparability across participating countries. It also includes the methods for data scaling, analysis, communication, and quality assurance to maintain the reliability and validity of the assessment data (OECD, 2024).

Using multilevel analysis, this study aims to investigate the effect that socio-demographic characteristics, specifically gender and socioeconomic status, as well as non-cognitive factors have on predicting the performance of Greek students in mathematics in the Programme for International Student Assessment data of the 2022 cycle.

## 2. Literature Review

### 2.1. Gender

Although numerous studies in the global literature examine the role of gender in educational outcomes, there is still disagreement regarding the importance of gender in student achievement in mathematics (Karakolidis et al., 2016; Pitsia et al., 2017; Reilly et al., 2015, 2019; Samuelsson & Samuelsson, 2016). Although boys outperformed girls in mathematics in the 1990s, the gap between the two genders in mathematics achievement appears to have narrowed in the last decade, with most studies only reporting a very small performance advantage in favor of the boys (Contini et al., 2017; Reilly et al., 2019) or concluding that there are no longer any significant gender differences in mathematics achievement (Else-Quest et al., 2010; Karakolidis et al., 2016; OECD, 2023b; Pitsia et al., 2017; Reilly et al., 2015).

As a cause of these differences, theorists tend to include a lack of effective female role models (Beilock et al., 2010) and gender preferences for different teaching approaches (Rodd & Bartholomew, 2006). Despite evidence demonstrating women's capability in mathematics, it also remains a widespread stereotype that mathematics is a male discipline in which women find it difficult to coexist (Alcock et al., 2014), making it more difficult to position themselves as successful mathematicians (OECD, 2016).

Researchers working on gender issues in mathematics share the goal of ensuring that no group of students is limited by societal expectations or deterred from further study and consequently seek to understand the specific factors that influence women's engagement with mathematics (Alcock et al., 2014). However, research shows that the relationship between gender and achievement is a relationship that is influenced by various factors, such as personality traits (Alcock et al., 2014), socioeconomic status (Cascella, 2020; Reilly et al., 2015, 2019), age and grade (Reilly et al., 2019), parental involvement (Reilly et al., 2019) and broader societal contexts (Cascella, 2020; Contini et al., 2017; Else-Quest et al., 2010; OECD, 2023b; Reilly et al., 2019), especially in countries where conditions of equality do not prevail, with women being disadvantaged in many areas of public and private life (Cascella, 2020) and education systems still characterized by inequalities (Karakolidis et al., 2016).

All these have systematic, measurable, and negative impacts on mathematical achievement and women's engagement in mathematical fields (Contini et al., 2017; OECD, 2016; Reilly et al., 2015, 2019), with PISA reporting that gender gaps in performance at age 15 may have long-term consequences for the personal and professional futures of girls and boys (OECD, 2016). Such gaps can reinforce "stereotype threat", a phenomenon in which individuals perform worse than their ability dictates on a task when a relevant negative stereotype is perceived during a performance test (Steele & Aronson, 1995). For PISA, gender equality is a fundamental value and goal of education policy, as an ethical principle linked to the concept of justice and a normative condition according to which, all people, regardless of their background, should have the opportunity to fulfil their potential (OECD, 2023b). According to PISA, boys outperformed girls in mathematics by nine score points in PISA 2022, while the gender gap in mathematics achievement did not change between 2018 and 2022 in most countries/economies, mainly because mathematics achievement declined for both boys and girls (OECD, 2023b). On average across OECD countries in 2022, 31% of boys and 32% of girls were considered low performers in mathematics, while around 11% of boys and 7% of girls were considered high performers in mathematics across OECD countries (OECD, 2023b).

### 2.2. Economic, Social and Cultural Status

Students' socioeconomic status [SES] remains a topic of great interest and concern for those studying its influence on education and student abilities (Armor et al., 2018; Cascella, 2020; Papanastasiou, 2002; Sirin, 2005) and child development (Bradley & Corwyn, 2002). The history of measuring socioeconomic status shows that SES is defined as a broad construct, composed of different components and measured by various indicators (Cowan et al., 2012; Lee et al., 2019; OECD, 2016; Sirin, 2005; White, 1982). Although socioeconomic status is measured by different variables in different studies, making it difficult to assess exactly what it is (Cowan et al., 2012; Lee et al., 2019; White, 1982), students' socioeconomic status has historically and across research been defined as:

> […] an individual's access to economic, social, cultural and human resources. Traditionally […] has included, as components, parental educational attainment, parental occupational status, and household or family income (Cowan et al., 2012, p. 14).

Socioeconomic status emerged as a concept in school life due to observations that students of parents with low income, low educational level or low-status jobs performed worse in school and on tests reflecting school performance (Cowan et al., 2012), but also from the belief that families with high socioeconomic status provide their children a range of services, goods, parenting actions and social connections that potentially benefit children, in contrast to children with low socioeconomic status (OECD, 2016).

Several studies have investigated which variables have been used in educational achievement studies to measure socioeconomic status (Bradley & Corwyn, 2002; Cowan et al., 2012; White, 1982). Taking into account the historical evolution of the concept of socioeconomic status, the main and most important variables-components of socioeconomic status are considered to be family income, parental educational level and parental occupational status (Cowan et al., 2012; Erola et al., 2016; OECD, 2016, 2023b; Sirin, 2005; White, 1982). The concept of socioeconomic status, however, is not unidimensional (OECD, 2016). Other component variables have been at the center of the debate as participants in the measurement of socioeconomic status, each with its own arguments and contradictions. One of them is home possessions (Cowan et al., 2012; Erola et al., 2016; OECD, 2016, 2023b; Papanastasiou, 2002; Sirin, 2005; White, 1982), which can either be an independent measurement variable or an additional measure of family income (Cowan et al., 2012). Another variable that is sometimes considered as a component variable in socioeconomic status is that of the socioeconomic status of the school the student attends (Armor et al., 2018; Cowan et al., 2012; Sirin, 2005) and is measured by averaging the total socioeconomic status of all students attending it (Cowan et al., 2012).

Regarding the relationship between academic achievement and socioeconomic status, research findings show that socioeconomic status has a positive effect on mathematics achievement (Armor et al., 2018; Coleman, 1966; Erola et al., 2016; Lee et al., 2019; Papanastasiou, 2002; White, 1982), with the magnitude of the effect varying, depending on how each study is conducted as well as demographic characteristics (Cascella, 2020; Lee et al., 2019; Sirin, 2005; White, 1982). At the same time, research has shown that school socioeconomic status also plays an important role in students' performance in mathematics (Armor et al., 2018).

Nowadays, large-scale international assessments usually include measures of socioeconomic status (Cowan et al., 2012). This is also the case in PISA, where:

> […] a student's socio-economic status is estimated by the PISA index of economic, social and cultural status (ESCS), which is derived from several variables related to students' family background: parents' education, parents' occupations, a number of home possessions that can be taken as proxies for material wealth, and the number of books and other educational resources available in the home (OECD, 2016, p. 205),

a definition that is consistent with more general definitions of socioeconomic status. The PISA economic, social and cultural status index is closely linked to other measures of socioeconomic status commonly used in the education literature (Avvisati, 2020) and allows for comparisons between students and schools with different socioeconomic profiles (OECD, 2016). The PISA ESCS index is considered internationally as a point of reference for measures of socioeconomic status in large scale assessments (OECD, 2023a).

A common and consistent finding across all PISA cycles is that socio-economic status is related to academic achievement at the educational system, school and student levels (OECD, 2016). This is also true for the cycle of 2022, where it was observed that socio-economically advantaged students (top 25% in their country on ESCS index) scored 93 points higher in mathematics than their socially, economically and culturally disadvantaged peers (bottom 25% in their country on ESCS index) on average across OECD countries (OECD, 2023b). At the same time, on average across OECD countries in 2022, a one-point increase in the PISA economic, social and cultural status index is associated with a 39-point increase in mathematics achievement, about twice the amount of typical knowledge acquired by 15-year-olds in one school year (OECD, 2023b).

It is worth noting that PISA has observed that, although student achievement is related to socio-economic status, this relationship is not deterministic, with previous evidence showing that some students can break the cycle of disadvantage, overcome the odds against them and achieve higher than expected based on their socio-economic status (OECD, 2023b). These students, called "*academically resilient students*", are defined in PISA as:

> […] students who are in the bottom quarter of the PISA index of economic, social and cultural status (ESCS) in their own country/economy but scored in the top quarter in that country/economy (OECD, 2023b, p. 119).

These students are characterized as academically resilient because, despite their socio-economic disadvantage, they have attained educational success compared to other students in their country (OECD, 2023b). On average across OECD countries, 10% of disadvantaged students scored in the highest quartile of mathematics achievement in their countries, making them academically resilient students (OECD, 2023b).

### 2.3. Non-Cognitive Factors

The term *"non-cognitive factors"* is used to contrast a variety of behaviors, personal characteristics, attitudes, and opinions with academic skills, abilities, and achievements (Gutman & Schoon, 2013; Robbins et al., 2004). It was introduced as a concept by sociologists (Bowles & Gintis, 1976; Robbins et al., 2004) to describe those factors that are not measured by scores obtained from cognitive tests. Although these factors have been labelled as non-cognitive, most of these constructs usually include significant cognitive elements (Messick, 1979). At the measurement level, a key distinction is that measures of cognitive domains are defined by correct and incorrect answers, while for non-cognitive domains, there are no correct answers, drawing conclusions based on the consistency of responses instead, or by using converging evidence and discrete cues (Messick, 1979). The domain of non-cognitive factors includes a very wide range of characteristics (Gutman & Schoon, 2013; Messick, 1979), including attitudes, interests, motivation, curiosity, self-concept, and creativity (Gutman & Schoon, 2013; Messick, 1979; Robbins et al., 2004).

#### *2.3.1. Attitudes*

*Attitudes* are a multidimensional concept that does not have a universal and clear definition, while any attempt of interpretation is carried out by various fields (psychology and education, among others) that focus on different aspects of the concept each time (Vandecandelaere et al., 2012). One of the most widespread definitions is the definition given by Zimbardo and Leippe (1991, p. 51), who define attitudes as:

> […] an evaluative disposition towards some object based upon cognitions, affective reactions, behavioral intentions, and past behavior that can influence cognitions, affective responses, and future intentions and behaviors.

The multidimensionality of the construct of attitudes lies between three key and interwoven components, which can also be seen in the definition of Zimbardo and Leippe (1991): The cognitive component, which contains responses that revolve around expressions of beliefs and perceptual reactions about the attitude object, the affective component, which contains expressions of feelings towards an attitude object or psychological reactions to an attitude object and finally, the behavioral component, which has to do with expressions of behavioral intentions and the overt materialization of those intentions with respect to the attitude object (Ajzen, 2005).

Attitudes are not an innate characteristic of individuals, but are formed after birth, during early childhood, through the social interactions and influences that individuals receive (Hannula, 2002; Sölpük, 2017). Attitudes are also not directly observable, but emerge indirectly through observable behaviors (Ajzen, 2005; Sölpük, 2017).

Regarding attitudes towards mathematics, researchers have proposed the existence of various dimensions that determine attitudes towards mathematics from multidimensional perspectives, with the most important being the enjoyment of engaging with the subject, the students' interest in that subject, and the students' perception of the value of the subject (Hwang & Son, 2021).

Determining the relationship between attitudes and academic achievement and the impact of that relationship is an important issue for the fields of social psychology and educational science (Sölpük, 2017). It has been observed that attitudes have a positive and moderate effect on students' achievement (Asiedu Menlah & Boateng, 2025; Hwang & Son, 2021; Karakolidis et al., 2016; Pitsia et al., 2017; Sölpük, 2017), with students' attitudes towards mathematics having a positive effect on students' academic achievement (Hwang & Son, 2021; Karakolidis et al., 2016; Sölpük, 2017; Wiberg, 2019).

#### *2.3.2. Self-efficacy*

*Self-efficacy* is a fundamental non-cognitive factor that can strengthen the other non-cognitive factors of students (Gutman & Schoon, 2013; Skaalvik et al., 2015). Regarding self-efficacy, Bandura (1989) states that it is a critical factor that influences the individual processes of an individual's abilities, referring to self-efficacy as:

> […] beliefs in one's capabilities to organize and execute the courses of action required to produce given attainments (Bandura, 1997).

Self-efficacy is essentially a judgment of individual abilities related to maintaining and regulating behaviors regarding achieving goals (Çikrıkci, 2017; Gutman & Schoon, 2013). Perceived self-efficacy plays a key role in shaping human behaviors (Çikrıkci, 2017), as it has a significant impact on the factors that determine it, such as goals, expectations, emotional tendencies and opportunities (Bandura, 2000).

Academic achievement and self-efficacy are reciprocally related (Gutman & Schoon, 2013; Skaalvik et al., 2015). Self-efficacy affects an individual's behavior— by guiding task choice and preference in that task, effort and persistence —and these behaviors, in turn, derive from individuals' beliefs about their capabilities and thus influence achievement. Conversely, performance outcomes feed back to recalibrate self-efficacy, reinforcing or weakening the beliefs that drive subsequent behavior (Çikrıkci, 2017; Gutman & Schoon, 2013; Skaalvik et al., 2015). For example, it is very likely that an individual who exhibits a cognitive and emotional behavior with a positive expectation of outcome, will complete the process successfully (Çikrıkci, 2017). At the same time, regarding academic achievement, individuals can determine, through self-efficacy, the behaviors that they need to demonstrate in order to achieve the desired result in difficult experiences or challenging contexts, such as academic exams (Çikrıkci, 2017; OECD, 2013a). Focused on the field of mathematics, self-efficacy refers to students' belief that they can successfully perform specific academic tasks related to mathematics (Schunk, 1991).

Regarding the relationship between academic achievement and self-efficacy, research findings show that self-efficacy has a positive and significant effect on achievement (Aviory et al., 2025; Çikrıkci, 2017; Karakolidis et al., 2016; Oppong-Gyebi et al., 2023; Pitsia et al., 2017; Skaalvik et al., 2015), with the change observed in the perception of self-efficacy of individuals being reflected accordingly in performance (Çikrıkci, 2017).

The relationship between self-efficacy and mathematics achievement has also been addressed in international large-scale assessments. For PISA, students who lack confidence in their ability to learn what they consider important and overcome difficulties are vulnerable to failure, not only in school but also in their adult lives (OECD, 2004). In line with previous cycles, there is a positive correlation in PISA 2022 between mathematics self-efficacy and mathematics achievement. Specifically, a one-point increase in the mathematics self-efficacy index is associated with an increase of 28 score points in mathematics on average across OECD countries and economies (OECD, 2024).

#### *2.3.3. Anxiety*

According to Spielberger et al. (1970), anxiety is defined as a particular tension, worry and increased nervous activity that is perceived at the level of consciousness. Anxiety related to education and learning is often defined as "exam anxiety" and is a form of anxiety that negatively affects students' achievement in exams and academic tests (Erzen, 2017). Research has shown that students experience higher levels of stress in subjects that involve numerical operations, such as mathematics and statistics, since these subjects require understanding and internalized thought processes, rather than simple memorization (Erzen, 2017). Thus, integrated into the context of mathematics, mathematics anxiety is defined as "[…] feelings of helplessness and stress when dealing with mathematics" (OECD, 2013b, p. 87). Many students experience intense math anxiety, resulting in them avoiding activities necessary to develop math skills, thus limiting future career choices that are directly related to the use and exploitation of math knowledge (Pitsia et al., 2017). However, math anxiety is not only a psychological phenomenon that negatively affects the ability to solve math problems. Individuals who experience it may also have a physical reaction to math, which can be likened to a pain sensation (OECD, 2013a).

The relationship between achievement and anxiety is bidirectional, negative and likely reciprocal (Erzen, 2017). For this relationship, research findings show that anxiety has a negative and significant effect on performance (Erzen, 2017; Karakolidis et al., 2016; Pitsia et al., 2017; Zhang et al., 2019).

The relationship between anxiety and achievement has also been a concern in international large-scale assessments. Mathematics anxiety was associated with lower performance across all education systems, regardless of socioeconomic characteristics, with international differences in the mathematics anxiety index accounting for approximately 25% of the variation in student mathematics achievement across countries and economies participating in PISA 2022 (OECD, 2023b). Specifically, it was observed that a one-point increase in the mathematics anxiety index corresponds to an 18-point decrease in achievement, considering the socioeconomic profile of students and schools (OECD, 2023b). Finally, it was observed that there was a negative relationship between anxiety and achievement in mathematics, with students feeling particularly anxious about their efforts and performance in mathematics, while there was a sharp increase since 2012 in the mathematics anxiety index in most OECD countries and economies (OECD, 2024).

## 3. Aim and Research Questions

This study aims to investigate the effect non-cognitive factors (specifically attitudes, self-efficacy and anxiety) have on the performance of Greek students in mathematics, in the PISA international educational assessment cycle of 2022. To address the aim mentioned above, we formulate the following research questions:

RQ 1) Do the non-cognitive factors presented above predict Greek students' achievement in mathematics in PISA 2022?

RQ 2) Which of these non-cognitive factors have the strongest role in predicting Greek students' achievement in mathematics?

RQ 3) To what extent do non-cognitive factors explain the variance initially observed at the student (within) and school (between) levels?

## 4. Method

### 4.1. Participants

To provide an overview of the sample analyzed, the data were extracted from a total of 6.403 15-year-old students from 230 schools, representing approximately 98.100 15-year-old students in Greece (approximately 91% of the total 15-year-old population of Greece) (OECD, 2023c). From this sample, 49.8% of the students were girls, while the remaining 50.2% (3217 students) were boys. Furthermore, Greek students' mean mathematics score (m = 430) in PISA 2022 was lower than the OECD average (m = 472), while in the Greek sample, boys statistically significantly outperformed girls by 6 score points on average.

### 4.2. Research Design

The present study, as a secondary analysis of publicly accessible data (https://www.oecd.org/en/data/datasets/pisa-2022-database.html), used the most recent data from the Programme for International Student Assessment, specifically the data from the 2022 cycle. Initially, data on student performance in mathematics - the dependent variable - were selected, which were derived from ten plausible values [PVs]. In large-scale assessments designed to monitor population trends, researchers typically focus on statistics like means, standard deviations, percentiles, and standard errors, among others. However, because these assessments sample only a small portion of the population, measurement error due to uncertainty is inevitable (Wu, 2005). One way to express the degree of measurement uncertainty at the individual level is to give each individual multiple scores that reflect the size of the error in the individual's estimate. These multiple scores constitute *plausible values* (Wu, 2005). Plausible performance values are essentially random values that arise from mathematically calculated (posterior) distributions of the values presented in the data (OECD, 2009). The methodology of plausible performance values consists of calculating - in a mathematical way - distributions around the reported values and assigning a set of random values from the calculated (posterior) distributions to each observed value. It is particularly important to note that plausible values do not represent the actual scores of students, but rather random numbers from the estimated distribution of scores that could reasonably be attributed to every student (Adams & Wu, 2003). Therefore, their use is not suitable for individual assessment and evaluation (OECD, 2009), but for large-scale assessment surveys such as PISA - since they better reflect population parameters (Wu, 2005), the purpose of which is to compare not just students as individuals, but as part of a wider group, in this case the representative whole of a country (OECD, 2009). Each student is assigned 10 plausible performance values for each domain, while for each statistical test, the statistical result is first calculated for each performance value, and then the average of the statistical results resulting from the 10 plausible performance values is calculated. Point estimates were averaged across the ten plausible values, and standard errors reflect both sampling variance (via replicate weights) and imputation variance across PVs, combined using Rubin's rules (OECD, 2009; Rubin, 1987).

In addition to the plausible performance values, *indicators* – essentially groups of variables that students have answered throughout the survey and provide information about a specific area – were used to analyze the research questions and include variables related to attitudes, self-efficacy and anxiety (OECD, 2009). To gather relevant information, PISA administers questionnaires to students that collect data on their family background, personal lives, and various aspects of schooling, teaching, and learning. The responses are analyzed together with assessment results to provide a more comprehensive and nuanced understanding of student, school, and education system performance (OECD, 2023a). Most of the questionnaire items were designed to be combined in such a way as to measure latent constructs that cannot be directly observed, through transformations or scaling procedures, leading to the construction of meaningful indicators (OECD, 2009). Students were asked to indicate their level of agreement or disagreement with the questionnaire statements, and these responses are used to determine how strongly they relate to the factors represented by the indicators, which are standardized with a mean of 0 and a standard deviation of 1 across all OECD countries. For the technical analysis of the data, these specific indicators were created due to the great interest that exists, as well as due to their usefulness and practicality (OECD, 2023a). Descriptions of the variables derived for the study's indicators are shown in Table 1.

Table 1
*Descriptions of the indicators used for the analysis*

| *Index* | *Derived Variables* |
|---|---|
| ESCS | Highest education of parents in years (PAREDINT)<br>Highest parental occupational status (HISEI)<br>Home possessions (HOMEPOS) |
| MATHEFF | A series of variables about how confident students felt about having to do a range of formal and applied mathematics tasks (ST290) |
| MATHEF21 | A series of variables about how confident students felt about having to do a range of mathematical reasoning and 21st century mathematics tasks (ST291) |
| MATHPREF | An index that captures whether students indicate they preferred mathematics over Test Language and Science from the answers in a series of variables (ST268) |
| MATHEASE | An index that captures whether students indicate they perceive mathematics as easier compared to the Test Language and Science from the answers in a series of variables (ST268) |
| FAMCON | A series of variables about how familiar students were with different mathematical concepts representative of different levels of mathematical skill or understanding (ST289) |
| MATHPERS | A series of variables about how often students engaged in behaviors indicative of effort and persistence in mathematics (ST293) |
| ANXMAT | A series of variables about students' agreement with statements about a range of attitudes that indicate anxiety towards mathematics (ST292) |
| SCHESCS | A variable derived from the average ESCS of all the students that are enrolled in a school and participate in the assessment |

### 4.3. Data Analysis

Data analysis is done by conducting *multilevel analysis*. Multilevel analysis is a statistical method for analyzing data of variation patterns (Snijders & Bosker, 2012). In multilevel analysis, the structure of the population is hierarchical, with the sample data also being hierarchical (Hox et al., 2010; Snijders & Bosker, 2012; Woltman et al., 2012). A better way to understand multilevel data is to realize that there is no single and appropriate level of data analysis, but all levels included in the data are important in their own special way (Hox et al., 2010). In educational research and specifically in PISA, the population consists of schools and students in those schools, and a two-stage stratified sampling design is applied; first, a sample of both public and private schools is selected, and then a sample of fifteen-year-old students is drawn from each selected school (Hox et al., 2010; OECD, 2024; Snijders & Bosker, 2012; Woltman et al., 2012). The advantages of multilevel modelling include the ability to analyze data and relationships between levels, the ability to predict the effects on a relationship, the adjustment for missing data, as well as the preservation of accurate estimates of effect size and standard errors.

The model constructed for prediction on hierarchical data is called a *multilevel model* or *hierarchical linear model* (Hox et al., 2010; Snijders & Bosker, 2012; Woltman et al., 2012) and uses students' achievement in mathematics as the dependent variable and the indicators stated as independent variables. In all variables, sampling weights were applied in accordance with OECD recommendations for the PISA survey and as presented in the chapter by Karakolidis et al. (2022) and the analytical framework for PISA 2022 (OECD, 2023a).

## 5. Findings

For the analysis of the factors mentioned above, a two-level multilevel model was conducted, with students at the within level and schools at the between level, to investigate the contribution of both student-level and school-level variables in explaining the variance in mathematics achievement. All multilevel analyses were performed using Mplus version 8 (Muthén & Muthén, 2017). The analysis was developed starting from the null model, which is the simplest model, and systematically progressing to models with more variables (Hox et al., 2010). The simplest linear model (1) does not take the hierarchical nature of the data into account. For this purpose, a random effects model was created (2):

$$MathScore = 429.989\ (3.191) + e_{ij} \quad (1)$$

where $\beta_0$ = 429.989 (3.191) is the fixed mean (intercept) of the dependent variable and $e_{ij}$ are the student-level residuals.

$$MathScore = 411.573\ (5.490) + u_{0j} + e_{ij} \quad (2)$$

where $\beta_0$ = 411.573 (5.490) is the fixed mean (intercept) of the dependent variable, $u_{0j}$ is the effect of school ($_j$) on the dependent variable, and $e_{ij}$ are the student-level residuals.

The null model was fitted in order to detect whether there were statistically significant differences between schools and therefore whether it is worth fitting a multilevel model. To test the significance of the effects at the school level, a likelihood ratio test was conducted to compare the null random effects model with the null single-level model. The likelihood ratio test was calculated as the difference in the $-2$**loglikelihood values* for the two models. In this case, the $p$-value is less than the statistical significance level (LR = 41.422, $p < .001$) and therefore it makes sense to include the school level in our model, since there are statistically significant differences between schools. The between-level variance in the null random effects model was $\sigma_u^2$ = 2466.198 ($SE$ = 424.438), while the within-level variance was $\sigma_e^2$ = 4933.672 ($SE$ = 133.889). From these, it can be deduced that the total unexplained variance of the model was $\sigma_u^2 + \sigma_e^2 = 7399.870$, a result obtained by adding the variations both at school and student level. The percentage of unexplained variance at each level (Intra-class Correlation – ICC) is obtained by dividing the variance at each level by the total variance, as seen below:

$$\frac{\sigma_u^2 \ or \ \sigma_e^2 \ (Between\ level\ variance\ or\ within\ level\ variance)}{\sigma_u^2 + \sigma_e^2 \ (Total\ variance)}$$

Thus, the original model without the independent variables (null model) revealed an ICC of 0.332, which attributes 33.2% of the total variation in students' mathematics achievement to differences between schools, with the remaining 66.7% of the variation being attributed to differences between students. Although differences between students seem to play the largest role in their performance, differences between schools seem to play an equally important role in student achievement and should not be overlooked.

The model explores the impact of non-cognitive factors on mathematics achievement in the PISA 2022 assessment, through a hierarchical process of variable introduction in five successive stages. The study's indexes derived variables are explained in Table 1. Table 2 presents the unstandardized (B) coefficients (along with standard errors) for each variable in the model, while for each stage of the model the fixed mean (intercept) of mathematics achievement is presented as well as the percentage of explained variation attributed at the school and student levels and the entirety of the model.

The variables of gender and social, economic and cultural status [ESCS] of the students were added in Stage 1. As can be seen from the results in Table 2 for Stage 1, boys score on average about 11 points higher in mathematics in the PISA survey than girls, a difference that is statistically significant, while the ESCS index of students also appeared to be a significant predictor of mathematics achievement, with a one-point increase in the ESCS index of students, corresponding to an increase of approximately 17 score points in mathematics achievement. The model up to Stage 1 explains approximately 9.3% of the total variance (~3.7% at the student level and 20.6% at the school level).

In Stage 2, variables were included that revolved around students' attitudes towards mathematics, specifically preference for mathematics (versus other subjects, MATHPREF), feeling of ease in mathematics (versus other subjects, MATHEASE), familiarity with mathematical concepts (FAMCON), and finally, effort and persistence in mathematics (MATHPERS). Of these variables, feeling of ease in mathematics (versus other subjects) did not appear to be a statistically significant predictor of mathematics achievement, while it was observed that students who showed increased effort and persistence to succeed in mathematics, preferred mathematics over other subjects and were familiar with mathematical concepts performed better than those who stated that they did not show the same degree of effort and persistence, nor the same preference or familiarity with mathematics. After adding attitudes, the model explains approximately 20.5% of the total variance, with ~8.8% explained at the student level and 44% at the school level.

In Stage 3, two variables that determine self-efficacy were added, self-efficacy in mathematical reasoning and 21$^{st}$ century mathematics (MATHEF21) and self-efficacy in formal and applied mathematics (MATHEFF). The analysis showed that self-efficacy in formal/applied mathematics played the most important predictive role of the two, with each unit in the self-efficacy index in formal/applied mathematics increasing mathematics achievement of Greek students in PISA 2022 by approximately 25 score points. In contrast, self-efficacy in mathematical reasoning problems, although a statistically significant predictor of mathematics achievement, appeared to have a negative impact on mathematics scores, with each unit in the self-efficacy index in mathematical reasoning problems decreasing performance by approximately 6 score points. It was also found that after the addition of self-efficacy in our model, the impact of ESCS becomes smaller, which is possibly attributed to the fact that students from higher socioeconomic backgrounds tend to have more resources and support, which leads to believing in themselves more. The model, after adding the self-efficacy factor, appeared to explain approximately 30.9% of the total unexplained variance (~18.4% at the student level, ~55.9% at the school level), with most of it explained by self-efficacy in formal/applied mathematics.

In Stage 4, the variable of mathematics anxiety (ANXMAT) was added as the last non-cognitive factor. As can be seen from this stage, students with higher mathematics anxiety record lower mathematics achievement than those who do not report increased anxiety. Specifically, an increase of one unit in the mathematics anxiety index leads to a decrease of approximately 9 score points in students' mathematics achievement in the PISA survey. At the same time, it was observed that math anxiety reduced the effects of all previous variables in the model, with gender and self-efficacy effects being reduced to a greater extent. The model after adding the variable of anxiety explains 31.75% of the total variance (~20.2% at the student level and ~55% at the school level).

Finally, the model is completed by adding the socioeconomic status of the school, which is observed to be a significant predictor of mathematics achievement, with a one-unit increase in the index of the social, economic and cultural status of the students' schools corresponding to an increase of approximately 38 score points in mathematics achievement. The final model explains 37.78% of the total variance (19.79% at the student level and 73.77% at the school level), with the strongest predictors being the socioeconomic background of the school and the students' self-efficacy in formal/applied mathematics. According to Cohen's (1988) guidelines regarding the magnitude of variance explained in multiple regression models, the effect size of the total variance explained in the final model is considered large, while the within level (student) variance corresponds to a medium effect and the between level (school) variance corresponds to a large effect. The final equation of the model is as follows:

$$MathScore_{ij} = \beta_{0j} + 5.950(2.761)Gender(Boys) + 8.888(1.311)ESCS + 1.683(3.477)MATHPREF + 2.798(4.212)MATHEASE - 1.323(1.150)FAMCON + 4.315(1.298)MATHPERS + 22.641(1.531)MATHEFF - 6.608(1.517)MATHEF21 - 9.152(1.487)ANXMAT + 37.835(6.270)SCHESCS + e_{ij},$$

where $\beta_{0j} = 418.034(3.916) + u_{0j}$

Table 2
*Multilevel model coefficients of non-cognitive factors in mathematics achievement*

| | Stage 1<br>B *(SE)* | Stage 2<br>B *(SE)* | Stage 3<br>B *(SE)* | Stage 4<br>B *(SE)* | Stage 5<br>B *(SE)* |
|---|---|---|---|---|---|
| **Gender** | | | | | |
| *Boys* | 10.623 *(2.627)** | 11.644 *(2.663)** | 9.236 *(2.731)** | 6.181 *(2.640)** | 5.950 *(2.761)** |
| **ESCS** | 17.105 *(1.577)** | 14.730 *(1.590)** | 11.521 *(1.456)** | 11.147 *(1.470)** | 8.888 *(1.311)** |
| **Attitudes** | | | | | |
| *MATHPREF* | | 7.805 *(3.867)** | 4.476 *(3.395)* | 2.016 *(3.406)* | 1.683 *(3.477)* |
| *MATHEASE* | | 9.170 *(4.670)* | 5.060 *(4.303)* | 1.658 *(4.212)* | 2.798 *(4.212)* |
| *FAMCON* | | 4.146 *(1.155)** | −0.644 *(1.120)* | −1.336 *(1.138)* | −1.323 *(1.150)* |
| *MATHPERS* | | 11.582 *(1.251)** | 5.410 *(1.311)** | 4.500 *(1.311)** | 4.315 *(1.298)** |
| **Self-Efficacy** | | | | | |
| *MATHEFF* | | | 25.290 *(1.577)** | 23.135 *(1.542)** | 22.641 *(1.531)** |
| *MATHEF21* | | | -5.943 *(1.521)** | −6.987 *(1.535)** | −6.608 *(1.517)** |
| **Anxiety** | | | | −9.036 *(1.511)** | −9.152 *(1.487)** |
| **School ESCS** | | | | | 37.835 *(6.270)** |
| **Intercept** | 408.245 *(5.367)* | 414.314 *(4.807)* | 418.485 *(4.475)* | 420.460 *(4.466)* | 418.034 *(3.916)* |
| **Explained Variance ($R^2$)** | | | | | |
| Within-Level (Student) | 3.67% | 8.86% | 18.37% | 20.16% | 19.79% |
| Between-Level (School) | 20.6% | 44% | 55.88% | 54.94% | 73.77% |
| Total Variance Explained | 9.32% | 20.57% | 30.87% | 31.75% | 37.78% |

*Note.* *Statistically significant predictor.

## 6. Discussion

The purpose of this study was to investigate the impact of non-cognitive factors on student achievement in mathematics, using the data of the Programme for International Student Assessment 2022 in Greece. The findings of this study highlight the complex nature of these factors related to student achievement in mathematics. It was observed that, after accounting for other significant demographic variables, self-efficacy plays the largest role in predicting student performance (based on the unstandardized coefficients) (Çikrıkci, 2017; Karakolidis et al., 2016; Pitsia et al., 2017; Skaalvik et al., 2015), while attitudes (Hwang & Son, 2021; Pitsia et al., 2017; Sölpük, 2017) and anxiety (Erzen, 2017; Karakolidis et al., 2016; Pitsia et al., 2017; Zhang et al., 2019) play an equally important role, which is confirmed by the existing literature and by the results of the PISA assessment (OECD, 2023b). The multilevel model explained a substantial portion of the variance in mathematics achievement compared to the null model, accounting for approximately 73.7% of school-level variance and approximately 19.8% of student-level variance. That the multilevel model explains such a substantial share of school-level variance is a key result by itself, suggesting that the school environment plays a decisive role in influencing student outcomes. However, significant unexplained variance remained at both levels, indicating the need for further investigation into additional contributing factors, especially at the student level, where the large unexplained variance suggests the influence of other potentially relevant individual-level factors not included in the present analysis.

By highlighting the interaction between non-cognitive factors and mathematics achievement, this study extends existing research and clarifies the relative weight of these factors within the Greek educational setting. The central finding of self-efficacy (in formal and applied mathematics) being the most important non-cognitive predictor of mathematics achievement reinforces the well-established role of mathematics self-efficacy as a powerful determinant of mathematics achievement (Çikrıkci, 2017; Karakolidis et al., 2016; Pitsia et al., 2017; Skaalvik et al., 2015), with mathematics self-efficacy for formal and applied mathematics tasks having the biggest effect on mathematics achievement, even after accounting for other sociodemographic and non-cognitive variables. An interesting nuance in our findings is the divergent predictive behavior of the two self-efficacy indicators. While self-efficacy for formal and applied mathematics tasks was a strong positive predictor of achievement, self-efficacy in mathematical reasoning and 21st-century mathematics exhibited a negative coefficient. While diagnostic checks confirmed that strict multicollinearity was not an issue (Variance Inflation Factor < 10 and Tolerance > 0.1 for both variables), entering both into the same model isolates their unique effects: once the model accounts for the primary variance captured by formal mathematics self-efficacy, the residual variance in reasoning self-efficacy negatively correlates with achievement. This statistical behavior reflects a specific reality of the Greek educational context; Greek mathematics education and the highly influential shadow education system emphasize algorithmic and formal mathematics in preparation for high-stakes exams, thus explaining the positive assessment and effect of formal mathematics' self-efficacy. Consequently, if a student reports high confidence in abstract mathematical reasoning, a skill less explicitly trained, beyond what their formal math confidence would suggest, it may reflect on most occasions an overestimation of ability or an illusion of competence, ultimately corresponding to lower actual performance. At the same time, the positive correlation between Greek students' mathematics self-efficacy and their mathematics achievement was found to be weaker than that observed among students in other OECD countries. This pattern is consistent with Greece's comparatively lower average mathematics score relative to the OECD mean (OECD, 2024). However, this finding should be interpreted with caution, as the relationship between self-efficacy and achievement is reciprocal: while mathematics self-efficacy can predict achievement, students' performance in mathematics can, in turn, influence their self-efficacy (Çikrıkci, 2017; Gutman & Schoon, 2013; Skaalvik et al., 2015).

Furthermore, the present study confirms the significant and comparable impact of mathematics anxiety and student attitudes on mathematics achievement, underscoring the critical role of the affective domain in learning. Our results are consistent with a large body of existing literature, demonstrating that anxiety can act as a significant barrier for the student's success (Erzen, 2017; Karakolidis et al., 2016; Pitsia et al., 2017; Zhang et al., 2019), a relationship that not only did stand after controlling for sociodemographic and other non-cognitive variables but also interacted with all the other variables and their relationships with mathematics achievement. This effect shows that mathematics anxiety is a pivotal non-cognitive factor that can have a negative effect on how other non-cognitive variables (like attitudes or self-efficacy) affect achievement, a finding that highlights the importance of managing and reducing anxiety, in order to unlock the positive effects of other factors like motivation, self-efficacy, and positive attitudes.

Lastly, it was also found that attitudes regarding mathematics were a significant predictor of mathematics achievement for Greek students, reaffirming their important but moderate role in shaping learning outcomes, as it is shaped in extensive literature research (Hwang & Son, 2021; Karakolidis et al., 2016; Pitsia et al., 2017; Sölpük, 2017). Effort and persistence in engaging in mathematical tasks emerged as a meaningful component of students' attitudes that contribute positively to mathematical achievement. Students who display a stronger willingness to persevere through challenging problems tend to achieve higher results, even after accounting for sociodemographic and other non-cognitive factors. As is the case with self-efficacy, the relationship between attitudes and achievement is reciprocal and thus should be interpreted with caution: while positive attitudes foster greater engagement and, as such, improved performance, higher achievement in mathematics can, in turn, strengthen students' attitudes and confidence toward the subject.

## 7. Recommendations for Educational Policy

The findings of this study have important implications for educational practice and policy. The strong relationship observed between attitudes and self-efficacy on one hand and mathematics achievement on the other highlights the necessity of cultivating students' confidence in their abilities in order to enhance engagement. Self-efficacy and positive attitudes act as proximal factors of task choice, preference, effort, persistence and strategic use, with students who believe they can succeed and who view mathematics as an interesting and useful subject, being more likely to choose and tackle challenging problems, persist through setbacks, and learn more effectively. Accordingly, classroom practices and educational policies that provide and prioritize mastery experiences and feedback addressing both cognitive and non-cognitive dimensions, normalize productive errors and model effective strategies may help strengthen both attitudes and self-efficacy, fostering a virtuous cycle of non-cognitive engagement and achievement. Specifically, teachers can incorporate instructional scaffolding, breaking complex problems into manageable steps to minimize cognitive overload and provide immediate, constructive feedback that focuses on the process of solving the problem rather than just the final answer, thereby supporting students' self-efficacy and attitudes (Karakolidis et al., 2016; OECD, 2024; Pitsia et al., 2017; Skaalvik et al., 2015; Sölpük, 2017). Encouraging students to see challenges as opportunities for growth rather than obstacles could also enhance their engagement in the learning process and, consequently, their performance. At the same time, integrating everyday life mathematical concepts, promoting collaborative learning environments and strengthening support in order to cultivate a growth-oriented mindset, can help foster positive perceptions and make mathematics more accessible and attractive. As a result of the above, students may be less likely to focus exclusively on performance-enhancing practices, but rather on the overall value of learning, helping them to see progress as a continuous process of improvement and achievement. For PISA, school systems need to ensure that students not only have the necessary knowledge to continue learning mathematics after formal schooling, but also the interest that may encourage them to do so (OECD, 2013a).

Furthermore, the significant impact of anxiety in mathematics requires targeted interventions, such as anxiety management practices (expressive writing interventions, cognitive reappraisal techniques) by specialized staff, that could support students overcome any insecurities they may have and approach mathematics with greater confidence (Gutman & Schoon, 2013; Pitsia et al., 2017), while the school environment should be freed from practices that intensify anxiety and adopt teaching methods that encourage a positive attitude towards mathematics, through the creation of a supportive learning environment, emphasizing not only on the outcome but on the process of learning (Ashcraft & Krause, 2007). At the same time, teachers can also implement differentiated instruction through the use of game-like activities, technical and technological tools and collaborative tasks, which may lead to reducing the fear of failure that students have, enhancing learning engagement and cultivating positive emotions about mathematics (Boaler, 2016).

From an educational policy perspective, schools and education systems should prioritize the development of non-cognitive factors together with cognitive factors, as part of an integrated and holistic mathematics education framework that may be able to provide opportunities for the development and continuous reinforcement and encouragement of positive emotional relationships with mathematics. At the same time, these findings suggest that teacher training programs must go beyond content knowledge to include psychological pedagogical knowledge. Training should equip teachers with the tools to identify signs of high anxiety and low self-efficacy early. By addressing the specific psychological barriers of anxiety and self-doubt, educational systems could have a chance to move toward more equitable environments where students could be supported not just in what they learn, but in how they cope with the challenges of learning.

Through the highlighting of the correlations between various social and psychological parameters on the one hand and mathematics achievement on the other, the ability of the model to reveal factors whose strengthening can yield positive educational results cannot remain without practical and institutional continuity, something that is a crucial step in the attempt of creating more equitable and effective schools, in which all students will be able to have substantial opportunities for cognitive and psychosocial development. In this context, the findings of this study seek not only to describe, but also to actively contribute, through participation in the design of an education that aims to support the reduction of inequalities and the enhancing of learning achievements.

## 8. Conclusion

This study analyzed the impact of non-cognitive factors on Greek students' performance in mathematics through multilevel models, utilizing data from the international PISA 2022 assessment. The findings confirm the evidence regarding the significant impact of gender, socioeconomic background and non-cognitive factors such as attitudes, anxiety and self-efficacy on student achievement, with most independent variables included in the multilevel model explaining a significant amount of the variation of the dependent variable. Moreover, the findings indicated that educators, policy makers and schools should focus on students' non-cognitive factors when designing educational policies, programs and frameworks for the best possible shaping of the mathematics achievement.

## 9. Limitations

As with every research study, several limitations should be acknowledged when interpreting the findings. Firstly, it should be acknowledged that the nature of the PISA data does not allow the establishment of causal relationships between outcomes and variables (Goetz et al., 2010). Therefore, any correlation found between factors in mathematics achievement should be treated as indicative and not as proof of causality. At the same time, the data are based on information extracted from students' self-reports, making data prone to self-report response bias, which may be influenced by subjective perception, socially desirable response or limited self-assessment capacity, and therefore the findings resulting from such data should be interpreted with caution in terms of their reliability and validity, especially when they concern psychosocial and non-cognitive factors (Karakolidis et al., 2016; Pitsia et al., 2017). Finally, the study design also imposes limitations in terms of the generalization of the results since the data come exclusively from the Greek sample of the research, while the assessment framework concerns exclusively 15-year-old students. Therefore, the conclusions of this analysis cannot be generally extended to other age groups or to educational systems of different countries, which operate under different socio-economic, cultural and institutional conditions and regimes.

## 10. Future Studies

Finally, it is suggested to further examine the issue of non-cognitive factors as a continuation of this research. It has been observed in the literature that there is a significant interaction of individual, cultural and other factors in the relationship between non-cognitive constructs and achievement, making it appropriate to study such impacts (OECD, 2024; Pitsia et al., 2017; Samuelsson & Samuelsson, 2016; Skaalvik et al., 2015; Zhang et al., 2019), while, given the mixed findings on gender differences in the broader literature and the specific disparities observed in this sample, future studies should monitor these differences longitudinally, as well as employ mixed-methods approaches (integrating qualitative interviews or classroom observations) to investigate the specific social or pedagogical interactions that may discourage female engagement in mathematics despite equal capability. Moreover, while the current analysis focused on the direct effects of gender on mathematics achievement, future research should investigate potential interaction effects gender may have on the relationships between non-cognitive factors and student performance. Understanding these nuances is essential for developing equitable teaching strategies that address the specific psychosocial and educational needs of all students. Furthermore, future research could expand the range of non-cognitive factors examined. While this study focused on key non-cognitive predictors, other variables may also contribute to mathematics achievement. Investigating these factors in conjunction with those studied in our study could provide a more comprehensive understanding of the non-cognitive dimensions of academic performance and success. Similar future research and study is also encouraged, to clarify whether the findings obtained in this study were unique to the Greek sample of 15-year-old students and whether the findings are generalized in different groups, while the longitudinal investigation of these relationships could allow the detection of possible causal orderings of these constructs with mathematics achievement (Pitsia et al., 2017). Finally, future research should move beyond observational data to empirically test the practical recommendations (intervention studies, instructional strategies) outlined in this study, as to comparatively assess the efficacy of said recommendations.

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**Data Availability:** The data used in this study are publicly available from the Organisation for Economic Co-operation and Development (OECD). The PISA 2022 dataset can be accessed through the OECD's official website at: https://www.oecd.org/en/data/datasets/pisa-2022-database.html No proprietary or restricted data were used in this study.

**Declaration of Interest**: The authors declare no conflict of interest.

**Ethics Statement**: This study used secondary data from the PISA 2022 assessment conducted by OECD. All data are anonymized and publicly available. Ethical approval and informed consent were obtained by the original data collectors in accordance with the institutional and national research ethics standards. No additional ethical approval or consent was required for this secondary analysis.

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