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# Identifying key predictors of resilience in mathematics engagement: Global evidence from PISA 2022 using machine learning

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## Abstract

Students from socioeconomically disadvantaged backgrounds tend to show lower levels of mathematics engagement. However, some students demonstrate high mathematics engagement in the face of socioeconomic adversity. Understanding the factors that underpin such mathematics engagement resilience is crucial for advancing educational equity and quality. Drawing on the resilience framework of the Organisation for Economic Co-operation and Development (OECD), this study investigates key personal, familial and school-related predictors that distinguish engagement-resilient students from their non-resilient peers. Using the Programme for International Student Assessment (PISA) 2022 data from 80 economies, the analysis focuses on students in the bottom quartile of economic, social and cultural status ($N = 153{,}412$). Three ensemble machine learning models (i.e., Random Forest, XGBoost and LightGBM) were employed to identify the most important predictors among 115 variables, followed by accumulated local effects analyses to examine relationships between key predictors and mathematics engagement resilience. The results indicate that perseverance, curiosity, mathematics self-efficacy, lower mathematics anxiety and familiarity with mathematical concepts play central roles. Family support, teacher support, cognitively activating instruction, disciplinary climate and school size also emerge as important contextual factors. Accumulated local effects analyses further suggest pronounced non-linear patterns for key predictors, such as threshold effects and diminishing returns.

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These findings extend resilience research beyond academic achievement to mathematics engagement and provide evidence to inform targeted interventions for disadvantaged students.

**KEYWORDS**
machine learning, mathematics engagement, PISA 2022, resilience

**Key insights**

**What is the main issue that the paper addresses?**

This paper examines mathematics engagement resilience among socioeconomically disadvantaged students. Moving beyond achievement-focused resilience research, it investigates the predictors of mathematics engagement resilience and how key predictors are associated with students‘ likelihood of being classified as engagement resilient, using a machine-learning approach to capture complex and potentially non-linear patterns.

**What are the main insights that the paper provides?**

This study identifies a multi-level set of predictors of mathematics engagement resilience. Individual factors, including perseverance, curiosity, mathematics self-efficacy, low mathematics anxiety and familiarity with mathematical concepts, were among important predictors. Contextual factors, such as family support, mathematics teacher support, cognitively activating instruction, disciplinary climate and school size, also emerged as important predictors. Accumulated local effects analyses further revealed non-linear patterns, including threshold effects and diminishing returns.

## INTRODUCTION

Mathematics engagement refers to students' involvement in mathematics learning and mathematics-related activities and can be understood as a subject-specific form of student engagement (Fredricks et al., 2004; Wang et al., 2016). Student engagement is widely regarded as a key process outcome in education, as it not only directly influences academic performance but is also closely related to students' long-term educational trajectories (Obrovská et al., 2025; Quintero et al., 2022). Because of limited economic and cultural capital within the family, students from lower economic, social and cultural status (ESCS) backgrounds tend to show lower levels of engagement (Chen et al., 2024; Mehan et al., 1996; OECD, 2010a). Nevertheless, not all students from socioeconomically disadvantaged backgrounds show low engagement. A proportion of these students are able to overcome adversity and maintain high levels of engagement (Bempechat & Shernoff, 2012). Drawing on the concept of academic resilience, which refers to students from low ESCS backgrounds achieving high academic performance (OECD, 2023b), we refer to these students as engagement-resilient students. Despite the well-documented importance of engagement,

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resilience research in education has largely focused on academic achievement, while engagement resilience has received comparatively little attention.

A growing body of research has examined factors associated with student engagement. For example, at the individual level, student perseverance has been shown to predict academic engagement (Obeng et al., 2025). At the family level, parental emotional support and attention to students' academic activities are associated with higher levels of engagement (Chen, 2008; Rickert & Skinner, 2022). At the school level, instructional practices play a critical role. In particular, cognitively activating instruction that encourages students to think deeply and reason is widely regarded as an important pathway to promoting engagement (OECD, 2024a). However, existing studies rely largely on traditional statistical approaches, such as structural equation modelling, which typically assume linear relationships among variables. As a result, these methods are limited in their ability to capture non-linear effects and to identify the most predictive factors from a large pool of potential influences (Wooldridge, 2010; Yarkoni & Westfall, 2017). Moreover, existing research on student engagement focuses relatively little on students in economically disadvantaged situations, which leads to an insufficient understanding of how disadvantaged students can achieve high levels of learning engagement.

The present study focuses on mathematics engagement resilience among socioeconomically disadvantaged students, defined as the capacity to maintain high levels of mathematics engagement despite socioeconomic adversity. Guided by OECD's (2018) resilience framework, this study systematically identifies key predictors of mathematics engagement-resilient students across individual, family and school levels. Using PISA 2022 data from 80 economies, three machine learning models are applied to handle a high-dimensional set of predictors. Accumulated local effects analyses are then used to illustrate the relationships between key predictors and the likelihood of being mathematics engagement resilient. Through this approach, the study extends resilience research beyond academic achievement to learning processes and provides more targeted empirical evidence to support sustained engagement among disadvantaged students.

# LITERATURE REVIEW

## Mathematics engagement

Before focusing on mathematics engagement, we first consider how student engagement has been conceptualised in the broader literature. Student engagement has been defined as "a metaconstruct encompassing multiple dimensions of involvement in school or commitment in learning" (Lam et al., 2012, p. 404). A substantial body of research has shown that student engagement not only positively predicts learning outcomes (Appleton et al., 2008; Bond et al., 2020), but is also associated with more positive learning attitudes (Joy et al., 2023), higher self-esteem (Liem & Martin, 2011) and greater life satisfaction (Lewis et al., 2011). In contrast, insufficient engagement is linked to a higher likelihood of poor academic performance and school dropout (Fall & Roberts, 2012; Wu et al., 2010).

Most researchers agree that student engagement is a multidimensional construct, although there is variation in how many dimensions are proposed (Fredricks et al., 2016). Researchers who supported a two-dimensional model argue that student engagement consists of behavioural engagement (such as effort, participation and persistence) and emotional engagement (including interest, enthusiasm and a sense of belonging, Finn, 1989). Some researchers have proposed a third dimension of student engagement, cognitive engagement, which includes self-regulation, investment in learning and the spending of metacognitive efforts (Fredricks et al., 2004). More recent studies have further identified social

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engagement as an additional dimension, referring to students' active interactions with peers and teachers (Wang et al., 2016).

These perspectives on generic student engagement provide a useful foundation for understanding engagement in specific subject domains. In this study, the focus is on mathematics engagement rather than on generic student engagement. Mathematics engagement refers to students' involvement when learning mathematical content or completing mathematics-related tasks. Mathematics engagement is not conceptually entirely distinct from generic student engagement. Rather, it retains the core meaning of generic student engagement while situating it in the specific context of mathematics learning. Although mathematics engagement retains the core meaning of generic student engagement, this subject-specific focus is crucial because mathematics engagement is influenced not only by cross-disciplinary factors, such as family support, but also by mathematics-specific factors, such as mathematics anxiety (Fredricks et al., 2004; Wang et al., 2016). These domain-specific influences make mathematics engagement a unique construct within the broader framework of student engagement. Like generic student engagement, mathematics engagement is also conceptualised as a multidimensional construct. OECD (2024a) measured mathematics engagement using eight items that capture behavioural, emotional, cognitive and social dimensions.

## Resilience in student engagement

The concept of resilience originated in physics, where it was used to describe the property of an object to return to its original size and shape after deformation (Oxford English Dictionary, 1989). After being introduced into psychology, resilience came to refer to the phenomenon in which individuals achieve positive outcomes despite exposure to significant adversity (Masten, 2001). According to this psychological definition, resilience involves two core elements: the presence of adversity and the attainment of positive outcomes. Adversity may take the form of socioeconomic disadvantage within the family (OECD, 2023b), parental mental illness (Werner & Smith, 1992) or experiences of abuse or neglect (Dong et al., 2003). Positive outcomes, in contrast, include high academic achievement (OECD, 2023b), good mental health (Kalisch et al., 2017) and harmonious interpersonal relationships (Luthar & Cicchetti, 2000).

Research on resilience in education has largely adopted the psychological perspective and has primarily focused on students from socioeconomically disadvantaged backgrounds who achieve high academic performance, a phenomenon commonly referred to as academic resilience (e.g., Zhang & Cutumisu, 2024; Zheng et al., 2024). However, resilience is not limited to academic outcomes alone. It also encompasses emotional, social and motivational domains (OECD, 2018). Student engagement represents a direct manifestation of motivation in the learning context (Flanagan & Symonds, 2021). Similar to the relationship between ESCS and academic achievement, students from lower ESCS backgrounds also tend to exhibit lower levels of engagement (Mehan et al., 1996; OECD, 2010a; Tomaszewski et al., 2020). This pattern may be explained, on the one hand, by limited parental involvement in learning due to constraints in time or resources, which is associated with lower engagement among disadvantaged students (Chen et al., 2024; Wang, Chen, et al., 2023). On the other hand, students from disadvantaged backgrounds are more likely to attend lower-quality schools and to be influenced by peers with lower levels of motivation, which may further suppress engagement (Wang et al., 2022). Importantly, not all students from low ESCS backgrounds show low engagement. Some are able to overcome adversity and demonstrate high levels of engagement (Bempechat & Shernoff, 2012). Previous research has shown that even among students with the lowest socioeconomic status, those who demonstrate high levels of engagement often outperform their peers from more advantaged backgrounds who display lower levels of engagement (OECD, 2002). In addition, even if students from low

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socioeconomic backgrounds do not qualify as academically resilient, maintaining high levels of engagement can still help sustain their quality of life during adolescence and enhance their chances of seizing employment opportunities (OECD, 2010a).

Resilience is widely understood as achieving positive outcomes despite adversity (Luthar et al., 2000), but there is no single agreed operational definition of either adversity or positive outcomes in educational resilience research. Different studies have defined adversity in different ways, such as socioeconomic disadvantage (Wang & King, 2025), abuse or neglect (Dong et al., 2003) or immigrant background (OECD, 2018). To qualify as adversity in resilience research, the selected risk factor should be negatively associated with the positive outcome under consideration (Fergus & Zimmerman, 2005). In the present study, socioeconomic disadvantage was selected as the adversity criterion because prior research has consistently shown that it is negatively associated with student engagement (Mehan et al., 1996; OECD, 2010a; Tomaszewski et al., 2020). The operationalisation of positive outcomes also varies across studies. Most quantitative studies define resilience using a cut-off that distinguishes relatively high from relatively low outcomes (Ye et al., 2021). Some use a fixed benchmark, while others adopt a relative threshold such as the top one-third or top one-quarter of the distribution (Sandoval-Hernández & Białowolski, 2016; Ye et al., 2021). In the present study, we adopted a quartile-based definition for three reasons. First, this aligns with OECD/PISA reports from 2009 onwards, which have consistently used quartile-based thresholds to define resilience (OECD, 2010b, 2013, 2016b, 2019, 2023b). Although the OECD's initial PISA 2006 analysis used a one-third threshold, later PISA reports have adopted a one-quarter threshold. By adopting a quartile-based definition, the present study enhances its comparability with existing PISA literature and related policy discussions. Second, compared with a one-third cut-off, a one-quarter threshold provides a more stringent criterion for identifying disadvantaged students with clearly high levels of mathematics engagement. Third, compared with a fixed benchmark, a quartile-based definition ensures that each economy includes a meaningful proportion of engagement-resilient students, which helps maintain sufficient analytical sample sizes across economies (OECD, 2011).

Based on the above considerations, and drawing on OECD's (2023b) definition of academic resilience, engagement-resilient students are defined in this study as those whose economic, social and cultural status falls within the bottom 25 percent within their respective economies, while their levels of mathematics engagement rank in the top 25 percent among all students in their respective economies. The remaining students from the bottom ESCS quartile are classified as non-resilient students.

## Theoretical framework

The Risk and Protective Factors Model provides a foundational framework for understanding resilience (Fergus & Zimmerman, 2005; Garmezy et al., 1984; Roberts, 2026). Risk factors refer to conditions that substantially increase the likelihood of maladaptive outcomes, such as prolonged poverty, natural disasters or family violence. Protective factors, in contrast, are resources that buffer negative effects and promote positive outcomes under conditions of risk. These protective factors are commonly categorised into individual resources, family resources and extrafamilial resources (Masten & Coatsworth, 1998). Building on this model, OECD (2018) proposes a resilience framework in which resilience is conceptualised as the result of factors operating at multiple levels, including the individual, family, school and system levels.

The present study adopts this OECD framework and focuses primarily on the individual, family and school levels, as factors at these levels are most closely related to student engagement (Fredricks et al., 2004). At the individual level, a range of personal characteristics have been shown to support mathematics engagement. For example, mathematics self-efficacy

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has been identified as positively related to overall mathematics engagement, as well as to emotional, cognitive and social dimensions of mathematics engagement (Martin & Rimm-Kaufman, 2015; Miller et al., 2021). According to self-efficacy theory, individuals' beliefs about their capabilities strongly influence their effort and persistence when facing challenges (Bandura, 1977). Mathematics anxiety is also an important factor influencing mathematics engagement. Previous research has shown that students with higher levels of mathematics anxiety reported lower cognitive-behavioural and emotional engagement in mathematics (Quintero et al., 2022). This may be because mathematics anxiety evokes feelings of worry, tension and distress, thereby discouraging students from actively engaging in mathematics learning (Luttenberger et al., 2018). In addition, students' familiarity with mathematical concepts may facilitate mathematics engagement by strengthening their mathematics self-concept (Granello et al., 2025; OECD, 2016a). At the family level, parents may influence engagement through expressions of support, encouragement and involvement in learning activities (Wu et al., 2014), such as assisting with homework (Bempechat & Shernoff, 2012). At the school level, both classroom processes and broader school characteristics have been linked to student engagement. With respect to classroom environments, teacher support is one illustrative factor that can promote engagement by satisfying students' basic psychological needs (Appleton et al., 2008). Beyond this, certain instructional practices in mathematics classrooms, such as cognitively activating instruction, have also been identified as beneficial for mathematics engagement, because such practices encourage students to persist in thinking and engage in deeper learning (OECD, 2024a; Zhang et al., 2021). At the broader school level, school size represents another example of a structural factor associated with engagement. Previous research suggests that students in smaller schools tend to show higher levels of engagement than those in larger schools (Leithwood & Jantzi, 2009).

## The present study

Despite the rich theoretical and empirical literature on both resilience and student engagement, several important gaps remain. First, most resilience research in education has treated academic achievement as the primary outcome of interest, while giving limited attention to disadvantaged students' active engagement in learning, which is itself a critical educational outcome (OECD, 2010a). Second, although numerous studies have identified factors associated with student engagement, few have examined how multiple factors jointly predict engagement within a unified analytical framework, particularly using machine learning approaches that can accommodate complex and non-linear relationships. Third, much of the existing evidence on student engagement is derived from single-country studies. In contrast, PISA provides large-scale, internationally comparable data, offering a unique opportunity to investigate engagement resilience across diverse educational systems.

Building on these gaps, the present study focuses on engagement resilience among students from low ESCS backgrounds across 80 economies participating in PISA 2022. Using three ensemble machine learning methods, namely Random Forest, XGBoost and LightGBM, this study explores which key factors distinguish engagement-resilient students from their non-resilient peers. In addition, accumulated local effects analyses are employed to examine how key predictors are related to the probability of being classified as engagement resilient. Accordingly, the study is guided by the following research questions:

1. Which key predictors distinguish mathematics engagement-resilient students from non-resilient students among students from low ESCS backgrounds?
2. How are key predictors associated with the probability of being classified as a mathematics engagement-resilient student among students from low ESCS backgrounds?

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# METHOD

## Data

This study draws on data from PISA 2022, conducted by OECD. PISA 2022 assessed the knowledge, skills, personal characteristics and learning environments of 613,744 15-year-old students enrolled in schools across 80 economies worldwide (OECD, 2023a). The present study focuses exclusively on students from socioeconomically disadvantaged backgrounds in order to examine engagement resilience under conditions of adversity. Following the OECD (2023b) definition of disadvantaged students, students whose ESCS falls within the bottom quartile within each economy are classified as socioeconomically disadvantaged. Applying these criteria, a total of 153,412 students from low ESCS backgrounds were included in the analytical sample.

## Measures

### Dependent variable

A binary dependent variable was constructed based on ESCS and the index of proactive mathematics study behaviour (MATHPERS), with MATHPERS used as an overall measure of mathematics engagement. ESCS is a composite index of students' economic, social and cultural status, derived from three indicators: highest parental occupational status (HISEI), highest education of parents in years (PAREDINT) and home possessions (HOMEPOS). HISEI is based on students' reports of their parents' occupations, which were converted into scores on the international socio-economic index of occupational status. The higher of the mother's and father's occupational status scores was then used to represent HISEI. PAREDINT represents the highest level of education attained by either parent, expressed in years of schooling. HOMEPOS reflects household possessions and educational and cultural resources available at home and was derived using item response theory (IRT) scaling. After HISEI, PAREDINT and HOMEPOS were obtained, the three ESCS components were standardised and averaged to create a preliminary ESCS score. The preliminary ESCS score was then standardised again to produce the final ESCS index (OECD, 2024a).

MATHPERS provides an overall measure of student engagement in mathematics (OECD, 2024a). It was derived from eight items modelled using IRT and captures multiple dimensions of engagement, including behavioural engagement (e.g., “I put effort into my assignments for mathematics class”), emotional engagement (e.g., “I lost interest during mathematics lessons”), social engagement (e.g., “I actively participated in group discussions during mathematics class”) and cognitive engagement (e.g., “I tried to connect new material to what I have learned in previous mathematics lessons”). Each item used a five-point response scale ranging from “Never or almost never” to “All or almost all of the time”. The eight items comprising MATHPERS are provided in Supporting Information (see Appendix C). Although student engagement can be theoretically distinguished into multiple dimensions, prior research suggests that a global measure of engagement is sufficient for addressing policy relevant questions related to student engagement (Wang et al., 2016). MATHPERS is consistent with previous operationalisations of mathematics engagement (Greene, 2015; Wang et al., 2016), and its reliability and validity have been established in the PISA technical documentation (OECD, 2024a).

Following OECD's (2016b) definition of academic resilience, engagement-resilient students are defined in this study as those whose ESCS falls within the bottom 25 percent within their respective economies, while their levels of mathematics engagement, as measured by MATHPERS, rank in the top 25 percent among all students in the same economy.

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These students were coded as 1 and comprise a total of 32,741 individuals. The remaining students from the bottom ESCS quartile were classified as non-resilient students and coded as 0, yielding 120,671 students.

### Independent variables

The selection of independent variables was guided by the Risk and Protective Factors Model and the OECD resilience framework (OECD, 2018; Roberts, 2026). According to the model and framework, engagement resilience is not expected to be explained by a single factor, but by multiple protective resources operating across individual, family, classroom and school levels. Therefore, rather than selecting only a small number of predictors in advance, this study adopted a comprehensive predictor set. The candidate predictors were all derived variables from the PISA student and school questionnaires that capture factors related to student learning, spanning the individual, family, classroom and school levels identified in the OECD resilience framework (OECD, 2023a, 2024a). This strategy allowed the analysis to examine how different levels of protective resources jointly distinguish mathematics engagement-resilient students from their non-resilient peers.

All derived variables from the student questionnaire and the school questionnaire were included as independent variables. After excluding duplicate variables, such as those representing the same construct, and variables with non-numeric formats, a total of 114 independent variables remained. In addition, given evidence that academic achievement may also contribute to student engagement (Lam et al., 2012), mathematics achievement, measured by PV1MATH, was included as an independent variable. Consequently, the final set comprised 115 independent variables. A complete list of the 115 independent variables, along with their descriptions, is provided in Supporting Information (see Appendix A).

## Data analysis

### Overview of the machine learning

Machine learning is a branch of artificial intelligence in which models automatically learn patterns from data to make predictions (Mitchell, 1997). In machine learning studies, data are typically divided into two parts: a training set and a test set. In the training set, the model has access to both the independent variables (also called features or predictors) and the dependent variable, allowing it to learn the relationship between them. In the test set, the model sees only the independent variables, and its task is to predict the dependent variable based on the patterns learned during training. The predicted values are then compared with the actual values to evaluate the model's performance (Hastie et al., 2009).

The most common and effective model type for structured (tabular) data is the tree-based ensemble model (Shwartz-Ziv & Armon, 2022), and all three algorithms used in this study belong to this family. Tree-based ensemble models are built on decision trees. A decision tree is a flowchart-like structure that splits the data into smaller groups according to the values of the predictors. As illustrated in Figure 1, the topmost node is the root node, representing the entire sample. At each internal node, the data are divided into branches based on a single predictor, and this process is repeated until a terminal leaf node is reached. In a binary classification task, each leaf contains both target and non-target observations, and the proportion of target observations in that leaf becomes the predicted probability for any new observation that falls into it. For example, in Figure 1, students are first split by their curiosity level (high vs. low). Within the high-curiosity group, they are further split by

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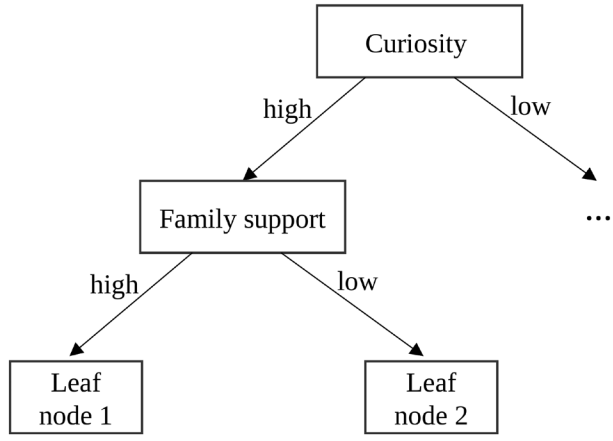



**FIGURE 1** Example of a decision tree.

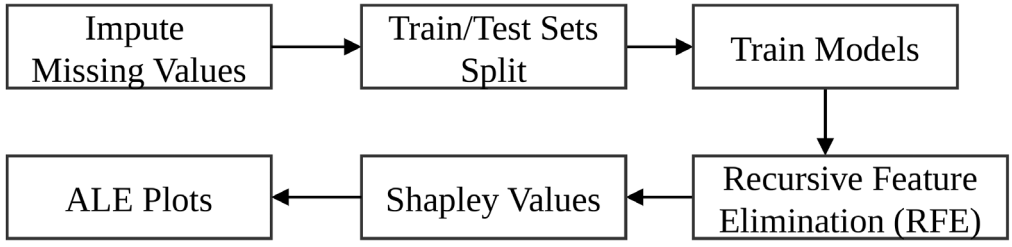



**FIGURE 2** Machine learning analytical workflow.

family support (high vs. low). For example, suppose leaf node 1 contains 70% engagement-resilient students, then any new student assigned to that node would be predicted to be engagement-resilient with a probability of 0.70. A single decision tree is relatively easy to interpret, but it can be unstable because small changes in the data may lead to very different tree structures. To overcome this limitation, ensemble methods combine many trees to produce more stable and accurate predictions. The three ensemble models selected in this study (Random Forest, XGBoost and LightGBM) differ in how they build and combine these trees (Hastie et al., 2009). A detailed explanation of their differences is provided in Section Primary analysis.

The overall analytical workflow is illustrated in Figure 2, and the analysis proceeded in six steps. First, missing values were imputed to ensure that students with incomplete data could still be included in the analysis. Second, the sample was split into a training set and a test set. Third, the models were trained on the training set. Within the training process, five-fold cross-validation was used. The training data were split into five equal parts. The model was trained on four parts and validated on the remaining part, and this process was repeated five times. As a result, each part served as the validation set exactly once. The purpose of cross-validation was to reduce dependence on a single data split and to obtain a more stable estimate of model performance during training. Fourth, we used recursive feature elimination (RFE) to select the most important predictors. RFE iteratively removes the least important predictor based on model performance until removing further variables would lower prediction accuracy, thereby reducing noise and improving interpretability (Zhang et al., 2023). Fifth, Shapley values were calculated for the selected features to rank their importance. Shapley values, derived from cooperative game theory,

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fairly attribute the contribution of each predictor to the model's predictions by averaging over all possible combinations of predictors (Rodríguez-Pérez & Bajorath, 2020). Finally, accumulated local effects (ALE) plots were used to show how the predicted probability of being an engagement-resilient student changes as the predictor increases. Instead of looking at a single data point, ALE plots estimate the average change in prediction within narrow intervals of that predictor. This approach provides a more reliable picture of non-linear relationships, as it accounts for correlations between predictors (Apley & Zhu, 2020).

Scientific inquiry can involve both explanatory and predictive approaches. Explanatory approaches, such as conventional linear regression, typically begin with theoretically specified hypotheses and use statistical significance testing to evaluate them. Predictive approaches, by contrast, place greater emphasis on identifying variables that improve the prediction of an outcome, especially when a large set of potentially relevant predictors is available (Longino, 2002; Yarkoni & Westfall, 2017). The present study follows this predictive logic. Its primary aim is not to test the independent statistical significance of each predictor, but to identify which predictors are most useful for distinguishing engagement-resilient students from non-resilient students. Nevertheless, given the theoretical orientation of educational research, we further interpret and discuss the key predictors identified by the machine learning models in relation to established theory and prior empirical findings in Section Discussion.

## Missing data

To reduce potential bias due to missing data, we applied iterative imputation by chained equations, in which each variable with missingness is imputed conditionally on the others in a round-robin fashion (Buuren & Groothuis-Oudshoorn, 2011). This approach is recommended and commonly used in applied research, including educational studies (e.g., Bouhlila & Sellaouti, 2013).

## Primary analysis

Three tree-based ensemble machine learning algorithms were employed, namely Random Forest, XGBoost and LightGBM. These algorithms combine multiple decision trees to improve predictive performance, stability and generalisability and have been widely used in educational data mining research (e.g., Zhang & Cutumisu, 2024; Zheng et al., 2025). Random Forest is an ensemble learning method that builds many decision trees and averages their predictions to make more stable and reliable predictions. During training, each tree is built using randomly selected data points and features, which helps reduce overfitting and makes the model more robust to noise in the data (Breiman, 2001). XGBoost is a model that builds decision trees in a sequence, with each tree trying to correct the errors made by the previous one. This process helps improve the model's performance, especially when working with structured data (Chen & Guestrin, 2016). LightGBM is another boosting method that builds trees by growing them one step at a time, focusing on the most important data points first. It is faster and uses less memory than XGBoost. LightGBM is especially suitable for datasets with a large number of features, large sample sizes and complex non-linear relationships (Ke et al., 2017).

All three selected algorithms belong to the family of tree-based ensemble models, which are recognised as particularly effective for analysing structured educational data (Fernández-Delgado et al., 2014; Shwartz-Ziv & Armon, 2022). In machine learning,

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generalisation error is primarily composed of bias and variance, which typically trade off against each other. Reducing bias often increases variance, and reducing variance often increases bias, with high bias leading to lower predictive accuracy and high variance increasing the risk of overfitting. Overfitting occurs when a model learns not just the underlying patterns in the data, but also the noise and random fluctuations, causing it to perform well on the training data but poorly on new data (Hastie et al., 2009). We deliberately chose these three models because they represent three distinct, complementary strategies for navigating the bias-variance trade-off. Random Forest emphasises variance reduction by constructing a set of deep, decorrelated trees through bagging and random feature selection (Breiman, 2001). XGBoost targets bias reduction by building trees sequentially, where each iteration is optimised to correct the residual errors of its predecessor under a regularised objective function (Chen & Guestrin, 2016). LightGBM further emphasises bias reduction compared to XGBoost, while mitigating the risk of increased variance through a leaf-wise tree growth strategy combined with gradient-based sampling (Bentéjac et al., 2021; Ke et al., 2017). Thus, these three algorithms are well-suited for structured data and target different regions of the bias-variance spectrum. Using them on the same data allows us to take advantage of their unique strengths while reducing the risks of relying on a single model.

During model training, the sample was stratified by dependent variable category and divided into a training set and a test set using a 7:3 ratio. Five-fold cross validation was conducted for each model. Final student weights (W_FSTUWT) were applied to account for the complex sampling design of PISA.

To address the first research question, recursive feature elimination (RFE) was used to identify the optimal feature subset for each model (Zhang et al., 2023). Feature importance rankings were then obtained based on Shapley values for each model (Rodríguez-Pérez & Bajorath, 2020). To improve the robustness of feature selection and reduce statistical noise through methodological triangulation, we retained only the predictors that were consistently identified as important across the three structurally different models (i.e., the intersection of the three optimal feature subsets). This cross-model convergence reduces the risk that a predictor is an artefact of any single model's instability (Denzin, 2009; Saeys et al., 2008). To address the second research question, ALE plots were employed to examine the relationships between key predictors and the probability of being classified as an engagement-resilient student. All analyses were conducted using Python 3.12.4.

## Model evaluation

Because the number of engagement-resilient students was substantially smaller than that of non-resilient students, resulting in an imbalanced class distribution with a ratio of approximately 1:3.69, classification accuracy may be misleading in this context (He & Garcia, 2009). For example, if most students are non-resilient, a model could achieve high accuracy simply by predicting most students as non-resilient, while still failing to identify engagement-resilient students. Accordingly, model performance was primarily evaluated using the area under the receiver operating characteristic curve (AUC). The receiver operating characteristic curve plots the true positive rate against the false positive rate across different classification thresholds (Fawcett, 2006). AUC represents the overall discriminative ability of the model and is independent of any specific classification threshold, making it particularly suitable for imbalanced classification problems (Bradley, 1997). In applied research, AUC values above 0.70 are generally considered indicative of acceptable classification performance (Šimundić, 2009).

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# RESULTS

## Model performance

After applying recursive feature elimination, the optimal number of features was identified for each model. Random Forest selected 20 features, XGBoost selected 30 features and LightGBM selected 35 features. All three models achieved AUC values above 0.70, indicating that each model successfully learned discriminative information relevant to identifying engagement-resilient students. Among the three models, Random Forest achieved the highest predictive performance, with an AUC of 0.7616, outperforming XGBoost (AUC = 0.7396) and LightGBM (AUC = 0.7480).

## Key predictors of engagement resilience

Twelve predictors were consistently identified as important across Random Forest, XGBoost and LightGBM. These common predictors are presented in Table 1. The optimal feature sets selected by each individual model are reported in Supporting Information (see Appendix B).

These twelve predictors spanned multiple levels, including individual, family and school factors, highlighting the multidimensional and complex nature of engagement resilience. We further examined mean differences in these predictors between engagement-resilient

**TABLE 1** Common predictors identified by the three models.

| Feature | Description | Engagement-resilient students M (SD) | Non-resilient students M (SD) |
|---|---|---|---|
| PERSEVAGR | Perseverance | 0.340 (1.058) | −0.192 (0.925) |
| CURIOAGR | Curiosity | 0.258 (1.106) | −0.168 (0.968) |
| MATHEFF | Mathematics self-efficacy: formal and applied mathematics | −0.265 (1.216) | −0.884 (1.128) |
| MATHEF21 | Mathematics self-efficacy: mathematical reasoning and 21st century skills | 0.305 (1.068) | −0.248 (0.965) |
| ANXMAT | Mathematics anxiety | 0.044 (1.207) | 0.437 (1.089) |
| FAMCON | Subjective familiarity with mathematics concepts | 0.740 (1.556) | −0.038 (1.405) |
| FAMSUP | Family support | 0.212 (1.155) | −0.284 (1.103) |
| TEACHSUP | Mathematics teacher support | 0.473 (1.164) | 0.085 (1.139) |
| COGACRCO | Cognitive activation in mathematics: Foster reasoning | 0.303 (1.230) | −0.132 (1.078) |
| COGACMCO | Cognitive activation in mathematics: Encourage mathematical thinking | 0.579 (1.164) | 0.069 (1.033) |
| DISCLIM | Disciplinary climate in mathematics | 0.192 (1.054) | −0.083 (0.997) |
| SCHSIZE | School size (Sum) | 790.043 (719.907) | 802.058 (732.035) |

*Note*: (1) Disciplinary climate in mathematics refers to students' perceptions of the frequency of classroom disruptions during mathematics lessons, including noise and disorder, students not listening to the teacher, delays in starting work, difficulty working well and distractions caused by digital resources. Because the items are reverse-coded in the PISA index, higher values of DISCLIM indicate fewer disruptions and a more positive disciplinary climate as perceived by students. (2) Means and standard deviations were calculated without applying weights.

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students and non-resilient students. With the exception of mathematics anxiety (ANXMAT) and school size (SCHSIZE), the remaining ten predictors exhibited higher mean values among engagement-resilient students.

At the individual level, engagement-resilient students reported higher levels of perseverance and curiosity, greater familiarity with mathematical concepts, lower mathematics anxiety and higher mathematics self-efficacy. At the family level, resilient students perceived stronger family support compared with their non-resilient peers. With respect to classroom experiences, resilient students were more likely to report a more positive disciplinary climate in mathematics classrooms, more frequent use of cognitively activating instructional practices and higher levels of mathematics teacher support. At the school level, engagement-resilient students tended to attend schools with smaller student populations.

It is also noteworthy that mathematics achievement (PV1MATH), although included as a candidate predictor, was not among the twelve predictors consistently identified across the three machine learning models. It appeared only in the optimal feature set selected by LightGBM, where it ranked 27th among 35 selected predictors, indicating relatively low importance. This suggests that engagement resilience was not simply captured by mathematics achievement.

## Relationships between key predictors and the probability of engagement resilience

Because the three machine learning models operated within different feature spaces, it was not feasible to jointly examine predictor effects across all models. We selected Random Forest to generate ALE plots. This decision was based on two considerations. First, Random Forest achieved the highest AUC among the three models, indicating the best predictive performance on our data. Second, as a bagging-based algorithm, Random Forest is generally less sensitive to local fluctuations in the data compared to boosting-based models (XGBoost and LightGBM) and therefore tends to produce relatively smoother and more stable ALE plots (Friedman, 2001; Hastie et al., 2009). Figure 3 presents ALE plots for these predictors.

At the individual level, the ALE curves for perseverance (PERSEVAGR), mathematics self-efficacy (MATHEFF and MATHEF21), familiarity with mathematical concepts (FAMCON) and curiosity (CURIOAGR) exhibited clear upward trends. As values on these predictors increased from low to high, the predicted probability of engagement resilience increased rapidly and then plateaued once values exceeded approximately two standard deviations above the OECD mean. In contrast, mathematics anxiety (ANXMAT) showed a pronounced downward trend. Higher levels of anxiety were associated with a lower probability of engagement resilience, with the steepest decline occurring below the mean. This pattern suggests that even relatively low levels of anxiety are meaningfully associated with engagement resilience.

At the family level, increases in family support (FAMSUP) were associated with a higher likelihood of engagement resilience. In particular, the predicted probability increased sharply once family support reached the OECD average.

At the classroom and instructional levels, mathematics teacher support (TEACHSUP), cognitively activating instruction that encourages mathematical thinking (COGACMCO), and a positive disciplinary climate (DISCLIM) were all positively associated with engagement resilience. Notably, although cognitively activating instruction aimed at fostering reasoning (COGACRCO) was also positively related to engagement resilience, its effect slightly declined when values exceeded approximately two standard deviations on the IRT scale.

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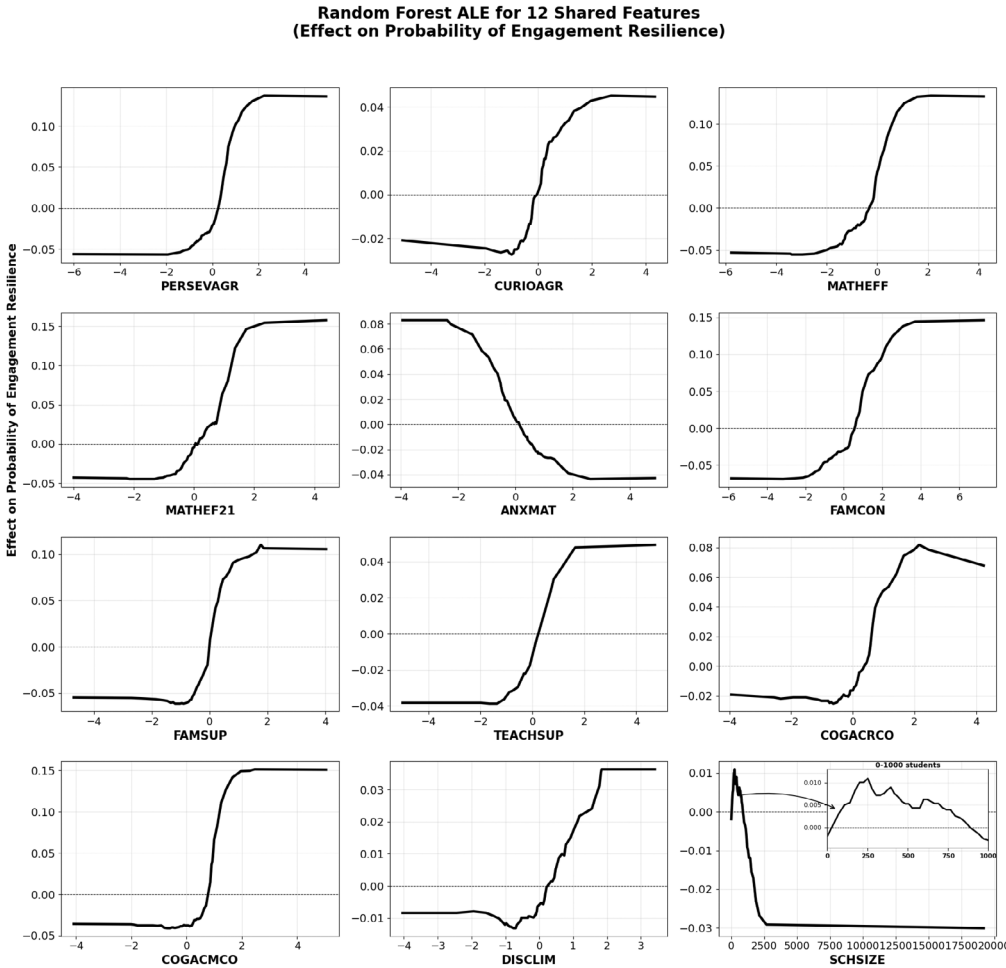



**FIGURE 3** ALE plots for twelve common predictors. (1) With the exception of SCHSIZE, all predictors were standardised using the OECD mean and standard deviation. A value of 0 represents the OECD average. (2) The vertical axis represents centred local marginal effects. A value of 0 indicates the average reference effect. Curves above 0 indicate positive contributions to the predicted probability of engagement resilience, whereas curves below 0 indicate negative contributions.

At the school level, the relationship between school size (SCHSIZE) and engagement resilience was clearly non-linear. Based on the numerical output of the ALE estimation procedure, the effect of school size first became positive at approximately 28 students, reached its maximum at around 251 students, and became negative after approximately 885 students.

## Comparison with a traditional logistic regression baseline

To examine the robustness of the predictive advantage of machine learning models, a logistic regression baseline was estimated using 12 common predictors. The logistic regression model yielded an AUC of 0.7384, which was lower than that obtained by the Random Forest, XGBoost and LightGBM models.

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# DISCUSSION

Using data from 80 economies participating in PISA 2022, this study focused on students whose ESCS ranked in the bottom 25 percent within their respective economies. By applying three ensemble machine learning methods, we identified key predictors that distinguish engagement-resilient students from non-resilient students and further examined how these predictors are associated with the probability of being classified as engagement-resilient using ALE analyses. Relative to a logistic regression baseline, the machine learning models demonstrated superior predictive performance, consistent with their ability to accommodate non-linear and interactive relationships that cannot be captured by logistic regression.

Interpreted through the Risk and Protective Factors Model and the OECD resilience framework, socioeconomic disadvantage represents the risk condition in this study, whereas the identified predictors can be understood as multi-level protective resources associated with high levels of mathematics engagement under socioeconomic adversity. Consistent with the resilience framework, which conceptualises protective factors as operating across individual, family and extrafamilial levels, these predictors span individual, family, classroom and school levels. As Ungar et al. (2013) noted, "resilience is not a characteristic of any single level of a complex system (neither the individual nor the institutions around them), but instead a dynamic attribute of the relationship between each element" (p. 350). Consistent with this perspective, our findings highlight the joint contributions of individual, family and school-level factors to student engagement resilience.

## Individual characteristics

Several individual-level factors were found to be important predictors of engagement resilience, including self-efficacy, socioemotional skills and familiarity with mathematical concepts. This finding is consistent with the resilience framework, which emphasises that individual resources can support positive adaptation under conditions of risk. Mathematics self-efficacy was positively associated with the probability of becoming an engagement-resilient student. When students report higher levels of self-efficacy, they tend to exhibit stronger academic motivation (Miller et al., 2021), which enables them to sustain effort and engagement despite barriers such as socioeconomic disadvantage, thereby increasing their likelihood of demonstrating engagement resilience (Gallagher, 2012).

Perseverance, curiosity and mathematics anxiety are closely related to socioemotional skills. Perseverance belongs to the task performance domain of socioemotional skills and showed a positive association with engagement resilience. Perseverance refers to the capacity to persist in tasks and activities until they are completed (OECD, 2021), a definition that inherently reflects the behavioural dimension of engagement. Moreover, perseverance is positively related to achievement motivation, and increases in perseverance may be accompanied by heightened motivation, which in turn promotes greater engagement (OECD, 2024b). Previous research has shown that perseverance not only directly predicts student engagement but also exerts indirect effects through motivation and self-regulated learning (Obeng et al., 2025). Curiosity, a socioemotional skill within the open-mindedness domain, refers to interest in and enjoyment of learning and exploration (OECD, 2024b). According to cognitive evaluation theory within self-determination theory, curiosity represents a prototypical form of intrinsic motivation (Deci, 1975), which serves as an important source of energy for student engagement (Chiu, 2022). Empirical studies have shown that curiosity is positively associated with deep learning strategies, reflecting cognitive engagement (Binu et al., 2020) and can positively predict emotional and behavioural engagement

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(Yang, 2025). Mathematics anxiety induces feelings of tension and distress (Luttenberger et al., 2018), which may lead students to avoid engagement in mathematics (Lau et al., 2024).

Familiarity with mathematical concepts also positively predicted the likelihood of engagement resilience, corroborating previous findings (Hoon et al., 2021). When students are more familiar with mathematical concepts, they tend to develop stronger mathematics self-concepts (OECD, 2016a), which in turn foster higher levels of behavioural and emotional engagement (Granello et al., 2025). Students from low ESCS backgrounds often have fewer learning opportunities and lower familiarity with mathematical concepts (OECD, 2016a). Our findings underscore the importance of conceptual familiarity in enabling disadvantaged students to maintain high levels of engagement.

It is also important to note that mathematics achievement played a limited role in predicting engagement resilience. Although it was included as a candidate predictor, it appeared only in the optimal feature set selected by LightGBM, where it ranked 27th among 35 selected predictors, indicating relatively low importance. This finding suggests that high engagement among low ESCS students cannot be understood simply as a by-product of high academic performance. Engagement resilience appears to represent a distinct form of positive adaptation, supported by socioemotional skills, mathematics-related beliefs and contextual resources. This is particularly important because students from low ESCS backgrounds often lack material resources and cultural capital, which contributes to lower academic performance (Tomaszewski et al., 2020). Our findings imply that even when disadvantaged students do not achieve exceptionally high academic performance, they may still maintain high levels of engagement. Such engagement may help sustain their quality of life during adolescence and improve their chances of seizing future employment opportunities (OECD, 2010a).

## Family factors

Compared with other family-related factors such as parental support for self-directed learning (FAMSUPSL) and family ICT resources (ICTRES) (see Appendix A in Supporting Information), family support emerged as the most salient family-level predictor of engagement resilience and was the only family variable consistently identified as important across all three machine learning models. Family support encompasses behaviours such as parents or family members talking with students, encouraging them to achieve good academic performance and showing interest in what they are learning (OECD, 2024a). Within the resilience framework, such support represents a family-level resource that may help buffer the risks associated with socioeconomic disadvantage. Consistent with prior research (Chen, 2008; Rickert & Skinner, 2022), our results indicate that engagement-resilient students reported levels of family support above the OECD average, whereas non-resilient students perceived lower than average family support. Parental communication, encouragement and expressions of interest in learning not only provide emotional reassurance but also convey the value placed on learning. Moreover, such support helps students feel that their academic efforts are shared and supported, which can foster resilience and motivate sustained engagement in learning activities (Li et al., 2023; Wu et al., 2014).

The ALE results further add nuance to this finding. The probability of engagement resilience increased sharply once family support slightly exceeded the OECD average. This suggests that, for students from low ESCS backgrounds, family support does not necessarily require intensive or time-consuming parental involvement. Even modest support above the average, such as regular encouragement, expressions of interest in learning and emotional reassurance, may be associated with a substantially higher likelihood of sustained engagement. This is particularly important because parents from low ESCS backgrounds often face

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greater family stress and resource constraints, which may limit the time and energy available for supporting their children's learning (Chen et al., 2024; Conger & Conger, 2002).

## Classroom factors

The resilience framework also highlights the importance of protective resources beyond individual and family domains, including extrafamilial resources located in classroom environments. Teacher support primarily refers to instructional structure and involvement. According to the self-processes model, teacher support satisfies students' basic psychological needs, thereby promoting engagement (Appleton et al., 2008). Our findings further suggest that cognitively activating instructional practices are beneficial for engagement resilience among disadvantaged students. Such practices inherently require active engagement, for example, encouraging students to persist when encountering challenging problems and to connect new mathematical content with prior knowledge, thereby stimulating behavioural and cognitive engagement (OECD, 2024a). Previous research has also shown that cognitively activating instruction predicts students' interest and perseverance (Zhang et al., 2021), both of which are conducive to engagement. However, our findings indicate that more of these practices is not necessarily better. The ALE results revealed that the positive association between cognitively activating instruction aimed at fostering reasoning and engagement resilience diminished once values exceeded approximately two standard deviations on the IRT scale. This finding contrasts with existing research, which generally assumes that more cognitively demanding instruction leads to better outcomes (Li et al., 2021). One possible explanation is that excessive demands for active reasoning may impose cognitive overload (Teig et al., 2018), which could be particularly challenging for low ESCS students with weaker academic foundations, potentially leading to heightened anxiety and avoidance of engagement. In addition, a positive disciplinary climate was positively associated with engagement resilience, likely because an orderly classroom environment allows students to focus more effectively on learning tasks (OECD, 2023c).

## School factors

The ALE results for school size revealed a clear non-linear pattern. As school size increased from very small to small and medium-sized schools, the probability of being classified as an engagement-resilient student increased. However, once school enrolment exceeded approximately 251 students, this positive association weakened. Leithwood and Jantzi (2009) summarised empirical evidence showing that students in smaller schools tend to exhibit higher levels of engagement, with low ESCS students benefiting more from smaller schools. However, our study, which focuses on low ESCS students globally, found that engagement resilience decreases when school size is too small. A possible explanation for this contradiction is that very small schools may face limitations in teacher quality and resources. Conversely, excessively large schools may also reduce student engagement, as they can undermine students' sense of belonging and constrain teachers' ability to provide individualised support. Both extremes may therefore be associated with lower levels of engagement (Scheerens et al., 2014).

Previous empirical studies may have been limited by methodological constraints, primarily considering the linear relationship between school size and engagement. Our study, using machine learning methods, overcomes this limitation by identifying a more nuanced, non-linear relationship that reveals the complexities of how school size affects engagement resilience among low ESCS students.

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Overall, when classified according to the resilience framework, the twelve key predictors were not evenly distributed across levels. Six were individual-level factors, one was a family-level factor, four were classroom-level factors and one was a school-level factor. Factors at the individual, family and classroom levels can be regarded as proximal variables, whereas the school-level factor can be regarded as a distal variable. Most of the identified predictors, therefore, belonged to proximal domains. This is consistent with previous research indicating that proximal factors are often more closely related to student development than more distal conditions (OECD, 2023a). This pattern suggests that proximal protective resources may be more frequently represented among the key predictors of engagement resilience than distal factors.

## IMPLICATIONS AND CONTRIBUTIONS

This study makes substantive contributions to the literature on student engagement and resilience at the theoretical, methodological and practical levels. First, prior resilience research based on PISA data has almost exclusively treated academic achievement as the sole outcome of interest (Cheung et al., 2024). However, resilience is not limited to academic performance alone (Southwick et al., 2014), but also encompasses multidimensional forms of adaptation, including motivation and emotional functioning (OECD, 2018). By operationalising engagement resilience as high levels of mathematics engagement among students from the bottom ESCS quartile within each economy, this study extends resilience research beyond achievement outcomes to the learning process and motivational domain. This shift offers a novel perspective for understanding how socioeconomically disadvantaged students differ not only in what they achieve but also in how they engage in learning.

Second, traditional resilience studies have largely relied on classical statistical approaches such as logistic regression, which are limited in handling high-dimensional data and tend to prioritise explanation over prediction (Yarkoni & Westfall, 2017). In contrast, this study applied machine learning methods to identify key predictors of engagement resilience from a pool of 115 variables that shape student learning. This approach is valuable because recent work on effect size magnification suggests that psychological and educational outcomes are rarely driven by a single key variable, but are usually shaped by multiple co-occurring influences (Gandhi et al., 2024). When research focuses on only one or a small number of predictors, it may unintentionally exaggerate their importance by neglecting other relevant influences. By examining a broad set of predictors simultaneously, this study reduces the risk of overstating the importance of any single factor and provides a more holistic understanding of the conditions associated with engagement resilience. By employing three ensemble learning algorithms and focusing on predictors consistently identified across all models, this approach also reduces the risk of algorithm-specific bias and false positive findings. Moreover, unlike many machine learning studies using large-scale educational datasets that report only feature importance rankings (e.g., Wang, King, & Leung, 2023), this study incorporated accumulated local effects analyses to provide a more nuanced visualisation and interpretation of the functional relationships between key predictors and engagement resilience.

Third, the findings of this study offer actionable insights for educational policy and practice. Among the twelve key predictors identified through machine learning, several are amenable to intervention or policy action, such as family support, teacher support, cognitively activating instruction, disciplinary climate and school size. In contexts where educational resources are constrained, policy and practice efforts may therefore prioritise these areas. For classroom practice, teachers can facilitate engagement resilience by providing support that satisfies students' basic psychological needs, together with orderly classroom

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environments that enable students to focus on learning. At the same time, the non-linear pattern for cognitively activating instruction aimed at fostering reasoning suggests that challenging instruction should be accompanied by appropriate scaffolding, particularly for low ESCS students who may have weaker academic foundations. At the family level, parents in low ESCS communities often face time constraints, financial pressure and family stress, which may limit their capacity to participate in intensive school-based involvement activities (Chen et al., 2024; Conger & Conger, 2002). Therefore, schools can make parental support more feasible by providing brief and accessible guidance during existing school events, such as school open days, or through low-cost communication channels such as text messages. Such guidance may focus on simple forms of support, including showing interest in what children are learning, encouraging effort and communicating confidence in children's ability to improve. Community organisations may also provide brief home-based parenting guidance, helping parents identify simple and feasible ways to support students' learning. At the school level, policymakers should pay attention to school size. For example, they may consider consolidating excessively small schools and reorganising overly large schools into smaller learning communities, so that students can receive more adequate resources, support and opportunities for sustained engagement.

## LIMITATIONS

Several limitations of this study should be acknowledged. First, the machine learning approach adopted in this study is inherently predictive rather than causal. Because PISA data are cross-sectional, the present analysis cannot establish causal relationships between the identified predictors and engagement resilience. In addition, although the use of 115 predictors enabled a broad examination of engagement resilience, this strategy also means that the analysis retains an exploratory component and may involve some risk of statistical noise. Therefore, the identified predictors should be interpreted as predictive signals rather than as causal determinants. Future research using longitudinal data would be valuable for clarifying the directionality of these relationships. Second, the present study operationalised engagement resilience using a quartile-based threshold. Although this approach is analytically useful, it simplifies a continuous construct. In particular, students with very similar levels of mathematics engagement may be classified differently if they fall on opposite sides of the cut-off. The findings should therefore be interpreted as applying to this operational definition of engagement resilience. Third, there are limitations related to the interpretability of machine learning models. Because the three machine learning algorithms operated within different feature spaces, accumulated local effects analyses were conducted only for the model with the highest AUC, namely Random Forest. While this strategy facilitated clearer interpretation, it also resulted in the loss of information from the other two models. Future research may consider more advanced techniques, such as ensemble stacking, to jointly integrate and interpret results across multiple algorithms (Hajihosseinlou et al., 2024).

## CONCLUSION

Using PISA 2022 data, this study provides the first depiction of engagement resilience among socioeconomically disadvantaged students across 80 economies. By applying machine learning methods in combination with accumulated local effects analyses, the study identified key predictors of engagement resilience operating at multiple levels. The results show that individual characteristics, such as perseverance, curiosity, low

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mathematics anxiety, self-efficacy and familiarity with mathematical concepts, together with contextual factors including family support, teacher support, cognitively activating instruction, a positive disciplinary climate and moderate school size, jointly increase the probability that students from low socioeconomic backgrounds maintain high levels of engagement in learning. Overall, this study extends the focus of academic resilience research from a sole emphasis on academic achievement to the learning process and motivational dimensions, highlighting the importance of multi-level coordinated interventions to create learning environments that support sustained engagement among disadvantaged students.

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## CONFLICT OF INTEREST STATEMENT
The authors have no relevant financial or non-financial interests to disclose.

## DATA AVAILABILITY STATEMENT
The data that support the findings of this study are openly available at the OECD website (https://www.oecd.org/en/data/datasets/pisa-2022-database.html).

## ETHICS STATEMENT
The study used publicly available and de-identified data from the Programme for International Student Assessment (PISA) 2022. Therefore, the study is exempt from ethical approval requirements.

## AI USAGE DECLARATION
ChatGPT (OpenAI) was used only to improve spelling and grammar. After using ChatGPT (OpenAI), the authors reviewed and edited the content as needed and take full responsibility for the content of the article.

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