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Understanding mathematics anxiety among high-achieving East Asian students: A machine learning analysis of PISA 2022 data

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ABSTRACT

Despite their exceptional performance in international assessments, students in East Asian regions report elevated mathematics anxiety in PISA 2022. This study applies XGBoost (Extreme Gradient Boosting), a machine learning algorithm, to analyze predictors of mathematics anxiety among 34,968 students across six East Asian regions (Singapore, Macau, Chinese Taipei, Hong Kong, Japan, and Korea) using PISA 2022 data. 26 key predictors were identified through recursive feature elimination. Shapley additive explanations were used to assess predictor importance, and partial dependence plots visualized nonlinear effects. Self-efficacy in mathematical reasoning and 21st century mathematics emerged as the strongest negative predictor, followed by general stress resistance. Mathematics achievement showed a weaker relationship, with anxiety decreasing only at very high scores. At school level, the total number of math teachers was most important, showing a nonlinear but generally positive association. Findings offer new insights into the complex drivers of anxiety in high-achieving educational contexts.

1. Introduction

Mathematics anxiety refers to worry, stress, or helplessness triggered by mathematics (OECD, 2015). Students with high levels of mathematics anxiety often perform poorly in mathematics and avoid math-related fields like STEM, limiting career options (Megreya et al., 2025; OECD, 2013).

In contrast to the general negative correlation between mathematics achievement and anxiety (OECD, 2023b), East Asian countries, known for their high academic performance, paradoxically report elevated levels of mathematics anxiety (Dowker et al., 2016). Specifically, Macau, Chinese Taipei, Hong Kong, and Japan reported anxiety levels above the OECD average in the 2022 Programme for International Student Assessment (PISA 2022). Even Singapore and Korea, although slightly below the OECD average in mathematics anxiety, scored higher than many lower-performing countries in anxiety levels (OECD, 2023b). The reasons for this paradox remain unclear, though factors such as self-efficacy, teacher support, and cultural influences have been suggested (Ahmmed et al., 2024; Gallagher, 2012; Leung et al., 2010). Many previous studies have examined predictors of mathematics anxiety in isolation or employed traditional statistical methods (e.g., linear models), which are limited by strong parametric assumptions and often fail to capture the complex, nonlinear relationships (Wooldridge, 2010). We note that current statistical modeling offers flexible extensions beyond simple linear models, such as generalized linear mixed-effects models and generalized additive models, which can accommodate hierarchical structures and nonlinear relationships. However, when the primary goal is out-of-sample prediction with many candidate predictors and potentially complex dependencies, these models often require substantial a priori specification of functional forms and interaction structures (Hastie & Tibshirani, 1986). As a result, these approaches may be less well aligned with a prediction-first objective in some high-dimensional contexts (Duarte et al., 2019).

Machine-learning methods, such as XGBoost, provide a prediction-first approach that can handle many correlated predictors and automatically learn nonlinearities and interactions without requiring substantial a priori specification of functional forms or interaction structures, often improving out-of-sample predictive performance (Chen & Guestrin, 2016; Friedman, 2001). Yet few studies have applied machine learning to investigate mathematics anxiety among East Asian students. This prediction-focused study employs XGBoost to analyze PISA 2022 data from six East Asian regions to identify key predictors of mathematics anxiety and to characterize how these predictors relate to students' predicted mathematics anxiety for decision-making purposes.

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Two research questions guided this study:

Research Question 1. What are the most important predictors of mathematics anxiety among East Asian students?

Research Question 2. How do these predictors relate to students' mathematics anxiety?

2. Literature review

2.1. Mathematics anxiety

Mathematics anxiety was defined as a single entity: "feelings of tension and anxiety that interfere with the manipulation of numbers and the solving of mathematical problems in a wide variety of ordinary life and academic situations" (Richardson & Suinn, 1972, p. 551). Subsequent research recognized its multidimensional nature, encompassing both cognitive worry and affective distress (Wigfield & Meece, 1988). Other scholars further distinguished between learning anxiety and evaluation anxiety (Plake & Parker, 1982). These dimensions are reflected in PISA 2022's six-item measure of mathematics anxiety (OECD, 2024a).

2.2. Predictors of mathematics anxiety

Many factors have been identified as predictors of mathematics anxiety. In this study, we categorize predictors into student-level and school-level factors.

2.2.1. Student-level factors

At the student level, mathematics self-efficacy has been consistently shown to be negatively associated with mathematics anxiety in some studies (e.g., Cuder et al., 2024; Rozgonjuk et al., 2020). According to Bandura's self-efficacy theory, students with low self-efficacy tend to perceive challenges as threats, thereby increasing anxiety (Bandura, 1977). Stress resistance refers to the ability to regulate anxiety and solve problems calmly. As it directly emphasizes the capacity to manage anxiety, stress resistance is considered a negative predictor of mathematics anxiety (OECD, 2024b). Regarding attitudinal dispositions, while some studies link self-directed learning to lower anxiety (Chang et al., 2021; Thamrin et al., 2018), others report no clear relationship (Aykurtlu et al., 2023). To clarify these inconsistencies, the present study includes this variable in a machine learning framework. According to the control-value theory, anxiety arises when students feel low control over learning (Pekrun, 2006). Therefore, students who perceive mathematics as easy and demonstrate proactive mathematics study behavior are more likely to develop a stronger sense of control, and may experience less anxiety (Doz et al., 2023; Quintero et al., 2022). A preference for mathematics reflects students' perceived intrinsic value, which can reduce mathematics anxiety (Broda et al., 2023; Muis et al., 2018). According to the reduced competency account, lower mathematics achievement is associated with higher mathematics anxiety (Ramirez et al., 2018). Finally, research has shown that greater familiarity with mathematical concepts is associated with lower levels of mathematics anxiety (Supekar et al., 2015), possibly because such familiarity enhances students' sense of control (Pekrun, 2006).

2.2.2. School-level factors

At the school level, a higher number or proportion of mathematics teachers may improve access to support, reducing students' anxiety (Wang et al., 2024; Yıldırım, 2012). By contrast, large school or class sizes may undermine students' sense of belonging and increase anxiety (Anderman, 2002; Štremfel et al., 2024).

Digital resource refers to students' availability of computers or tablets and schools' preparedness for digital learning. While digital resources may foster more positive attitudes toward mathematics and reduce anxiety (Atoyebi & Atoyebi, 2022), excessive exposure to electronic devices may increase distraction and stress (Pellas, 2024).

As for instructional climate, principal instructional leadership may reduce mathematics anxiety (Furner & Berman, 2003; Horne, 2022). However, negative student behaviors, such as truancy and alcohol use, may negatively affect the disciplinary climate and thus increase mathematics anxiety (Radišić et al., 2015). Mathematics extension courses may enhance student confidence, but their effects on anxiety are mixed (Baker et al., 2006; Cuder et al., 2024; Yi & Na, 2020). Finally, investment in teacher training and administrative capacity can indirectly alleviate mathematics anxiety (Horne, 2022; Turner et al., 2003).

2.3. Machine learning

Because this study is prediction-focused, we adopt machine learning to improve predictive accuracy and generalizability under a large set of candidate predictors (Yarkoni & Westfall, 2017). XGBoost, an optimized gradient-boosting machine learning algorithm, is particularly effective in handling missing data, multicollinearity, and complex feature interactions (Chen & Guestrin, 2016; Rusdah & Murfi, 2020). Given these strengths, this study adopts XGBoost to predict mathematics anxiety.

To enhance the interpretability of the machine learning model, this study applies SHAP (shapley additive explanations) to quantify the contribution of each predictor (Lundberg & Lee, 2017) and partial dependence plots to visualize their marginal effects (Friedman, 2001).

3. Methods

3.1. Data

This study utilized data from PISA 2022, focusing on six East Asian regions: Singapore, Macau, Chinese Taipei, Hong Kong, Japan, and Korea. The dataset includes responses from 34,968 15-year-old students (Singapore = 6606; Macau = 4384; Chinese Taipei = 5857; Hong Kong = 5907; Japan = 5760; Korea = 6454), along with linked school principal and parent questionnaires.

3.2. Measures

3.2.1. Response variables

Mathematics anxiety was measured using six items reflecting students' experiences of anxiety in mathematics-related contexts. Example items include: "I often worry that it will be difficult for me in mathematics classes," and "I feel anxious about failing in mathematics." Scores were estimated using item response theory (OECD, 2024a), with higher values indicating greater anxiety. Among East Asian students, standardized scores ranged from −2.39 to 2.64.

3.2.2. Features

Predictors were drawn from student-level and school-level data. Parent questionnaire variables were grouped under the student level, as they reflect students' family background characteristics. In PISA 2022, the student questionnaire included 86 derived variables, the parent questionnaire included 12, and the school principal questionnaire included 56. With the exception of the mathematics anxiety used as the outcome variable, all remaining derived variables were included as predictors in the analysis. Mathematics achievement (plausible value 1) was also included as a predictor. Variables with over 50% missingness were removed (Barton et al., 2023). Then, textual variables were excluded. Redundant variables (e.g., different labels for school type) were merged. Finally, student- and school-level data were matched via school ID, resulting in 118 predictors: 69 student-level and 49 school-level variables. Since this study is prediction-focused, all predictors are treated as concurrent features inputted simultaneously, without assuming any causal ordering or causal relationships among them.

3.3. Data analysis

We conducted all analyses in Python 3.12.4 (Python Software Foundation, 2024) using scikit-learn (Pedregosa et al., 2011; v1.6.1), XGBoost (Chen & Guestrin, 2016; v2.1.4), and SHAP (Lundberg & Lee, 2017; v0.47.1). The analysis included three stages. First, we removed features with zero variance, leaving 117 predictors, and applied recursive feature elimination (RFE) to identify the optimal feature subset (Zhang et al., 2023). A learning curve plotting the number of features against the explained variance (R^2) was used to determine the optimal number of features.

Second, we developed XGBoost model, which handles missing values via a sparsity-aware algorithm automatically (Rusdah & Murfi, 2020). The model was trained on the pooled dataset combining the six East Asian regions. The dataset was randomly split into a training set (70%) and a testing set (30%), and final student weights (i.e., W_FSTUWT) were applied to correct for non-response bias and sampling error caused by the two-stage stratified sampling design. Hyperparameters were tuned via randomized search and five-fold cross-validation to enhance predictive performance. The best-performing configuration was subsample 0.6, colsample_bytree 0.7, max_depth 8, n_estimators 300, learning_rate 0.01, reg_alpha 0, and reg_lambda 0.5. To address question 1, we used mean absolute SHAP value to estimate feature contributions. To address question 2, we constructed partial dependence plot (PDP) to visualize the marginal effects of key predictors on mathematics anxiety.

Third, we used root mean squared error (RMSE) and R^2 to evaluate model performance. A close match between training and testing performance suggests that the model is not overfitted and has good generalizability (Lever et al., 2016).

4. Results

4.1. Key predictors of mathematics anxiety

As shown in Fig. 1, the learning curve began to plateau after 26 features. At this point, the model's R^2 reached 26.35%, whereas including all 117 features only raised the R^2 to 28.48%, an increase of just 2.13%. To enhance efficiency and interpretability, we retained the top 26 most predictive features for model development. A more detailed learning curve (Fig. 2) further confirmed the robustness of this selection, showing that R^2 varied by only 0.64% when the number of features ranged from 26 to 31.

The XGBoost model achieved an RMSE of 0.9857 and an R^2 of 26.57% on the training set, and an RMSE of 0.9724 and an R^2 of 27.75% on the testing set, suggesting the model did not overfit and demonstrated good generalizability. Although the R^2 was moderate, it is comparable to or better than prior studies predicting affective outcomes from large-scale educational data (Wang et al., 2023).

Fig. 3 displays the mean absolute SHAP values of the 26 selected features. Table 1 provides detailed descriptions of these predictors, organized by category and sorted by importance. At the student level, the strongest predictors were MATHEF21, STRESAGR, and MATHEFF. Notably, STRESAGR, though not math-specific, ranked highly, highlighting the importance of general emotional regulation. While PROBSELF was among the top predictors, its counterpart SDLEFF ranked lowest, suggesting that self-directed learning affects anxiety mainly when difficulties arise. Interestingly, while mathematics achievement (PV1MATH) did have predictive power, it ranked second to last among the ten student-level features.

Among school-level features, TOTMATH and PROPMATH were the most predictive, indicating that math teacher staffing plays a role. Other school-related factors, such as digital preparedness (DIGPREP), instructional leadership (INSTLEAD), and disciplinary climate (STUBEHA), showed modest contributions.

Overall, student-level variables dominated in predictive power, reflecting the combined predictive contribution of psychological traits, academic background, and learning attitudes on mathematics anxiety.

4.2. Relationships between predictors and mathematics anxiety

Partial dependence plots (PDPs) were used to visualize the marginal effects of key predictors on mathematics anxiety (Figs. 4 and 5). At the student level, results showed clear non-linear trends for several features. MATHEFF displayed a threshold effect: anxiety declined sharply once self-efficacy reached the first third of the scale. Similarly, PV1MATH had little association with anxiety between scores of 400 and 550, but anxiety declined after scores surpassed 550. Since the OECD average of mathematics achievement in PISA 2022 was 472 and each proficiency level covers about 62 points (OECD, 2024a), this implies that anxiety begins to ease only after East Asian students exceed the OECD mean by one full proficiency level. SDLEFF exhibited a U-shaped pattern, with moderate levels predicting the lowest anxiety, while very high levels slightly increased it.

At the school level, TOTMATH, PROPMATH, and TOTAT were

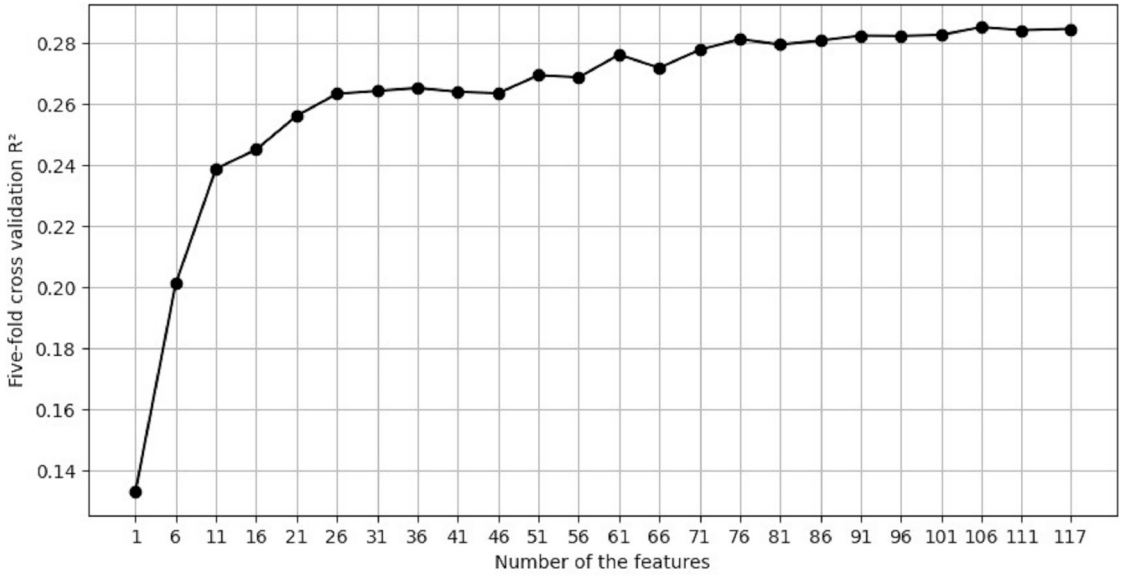


Fig. 1. The rough learning curve.

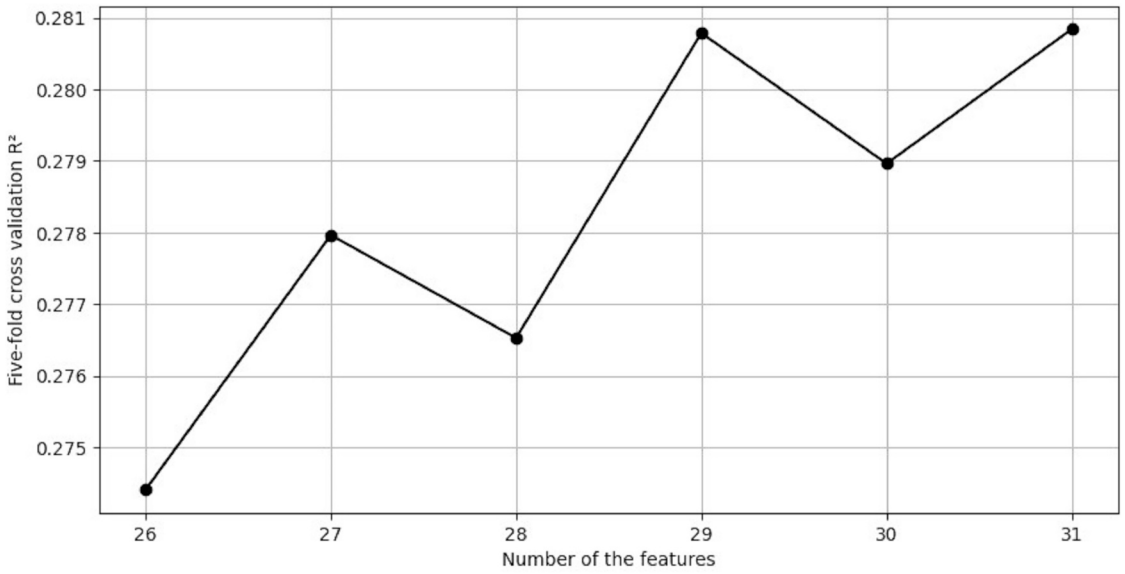


Fig. 2. The detailed learning curve.

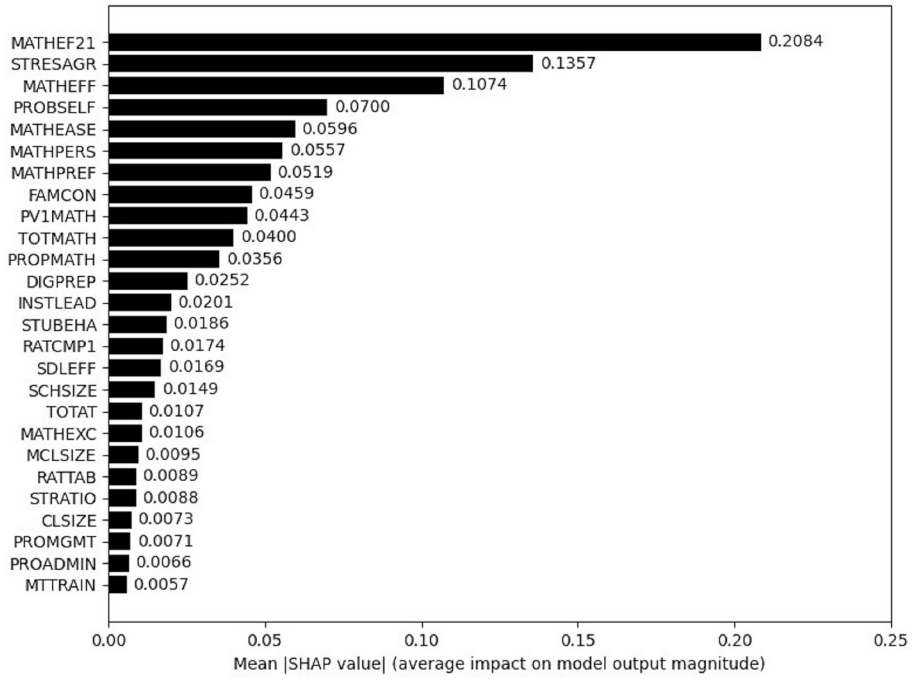


Fig. 3. Mean absolute SHAP values for features.

positively associated with anxiety at low to moderate levels, but plateaued or declined slightly at higher values. These variables correlated with SCHSIZE, which showed a small anxiety increase before leveling off. In terms of digital resource, DIGPREP showed a skewed S-shaped pattern when it was below the OECD average; however, once it surpassed the average level, mathematics anxiety rose steadily. RATCMP1 was linked to the lowest anxiety at a ratio of 0.2 but increased steadily beyond that, leveling off near 0.5. Interestingly, STUBEHA showed a negative relationship with anxiety. Finally, MATHEXC is a four-category variable, and partial dependence analysis showed that as long as schools offered differentiated extension courses, such as enrichment or remedial programs, students' mathematics anxiety increased compared to schools that offered no extension courses or provided additional mathematics instruction equally to all students. The remaining school-level features have SHAP values below 0.01, suggesting their impact on mathematics anxiety is negligible.

5. Discussion

5.1. The limited role of mathematics achievement

Although mathematics achievement is often considered a major determinant of anxiety (Ramirez et al., 2018), our results indicate it had relatively weak predictive power. PV1MATH ranked low among student-level predictors, and partial dependence analysis showed that anxiety remained high across scores from 400 to 550, decreasing only at higher levels. This pattern may reflect sociocultural pressures. All six East Asian economies examined share a Confucian heritage (Leung,

Table 1
Detailed description of 26 features.

Category	Feature	Description	Feature type
Student level	MATHEF21	Mathematics self-efficacy: Mathematical reasoning and 21st century mathematics	Continuous
	STRESAGR	Stress resistance	Continuous
	MATHEFF	Mathematics self-efficacy: Formal and applied mathematics	Continuous
	PROBSELF	Problems with self-directed learning	Continuous
	MATHEASE	Perception of mathematics as easier than other core subjects	Binary: 1 = Yes, 0 = No
	MATHPERS	Proactive mathematics study behaviour	Continuous
	MATHPREF	Preference of mathematics over other core subjects	Binary: 1 = Yes, 0 = No
	FAMCON	Subjective familiarity with mathematics concepts	Continuous
	PV1MATH	Plausible Value 1 in Mathematics	Continuous
	SDLEFF	Self-directed learning self-efficacy	Continuous
School level	TOTMATH	Total number of mathematics teachers at school	Continuous
	PROPMATH	Proportion of mathematics teachers at school	Continuous
	DIGPREP	Preparedness for digital learning	Continuous
	INSTLEAD	Instructional leadership	Continuous
	STUBEHA	Student-related factors affecting school climate	Continuous
	RATCMP1	Availability of computers	Continuous
	SCHSIZE	School size	Continuous
	TOTAT	Total number of all teachers at school	Continuous
	MATHEXC	Mathematics extension courses offered at school	Four-category: 0 = No additional math courses; 1 = Additional courses provided to all students regardless of grade; 2 = Either enrichment or remedial courses offered; 3 = Both enrichment and remedial courses offered
	MCLSIZE	Math class size	Nine-category
	RATTAB	Availability of tablet devices	Continuous
	STRATIO	Student-teacher ratio	Continuous
	CLSIZE	Class size	Nine-category
	PROMGMT	Proportion of school management personnel	Continuous
	PROADMIN	Proportion of school administrative personnel	Continuous
	MTTRAIN	Mathematics teacher training	Continuous

2001), where academic success is viewed not only as personal achievement but also as a form of family honor. These systems emphasize effort over innate ability, which can promote high performance but also lead to guilt or self-blame when students fall short (Stankov, 2010). Thus, even relatively high-achieving students may feel anxious if their performance fails to meet internalized expectations.

5.2. The central role of self-efficacy and self-regulation

Mathematics self-efficacy was the strongest negative predictor of anxiety, consistent with self-efficacy theory (Bandura, 1977). Students with high self-efficacy tend to feel more at ease when facing challenges, thus experiencing less anxiety (Gallagher, 2012). STRESAGR showed a strong negative correlation with mathematics anxiety. This finding supports the development of socio-emotional skills in schools to mitigate mathematics anxiety. The PDP for SDLEFF revealed a U-shaped relationship with anxiety. While moderate efficacy about self-directed learning was associated with the lowest anxiety, very high efficacy was linked to slightly higher anxiety compared to the minimum. Students with extremely high self-efficacy in self-directed learning may include perfectionists whose high standards contribute to anxiety despite their perceived capability (Flett & Hewitt, 2002).

5.3. Contextual effects at the school level

Several school-level variables related to SCHSIZE, including TOTMATH, PROPMATH, and TOTAT, were positively associated with mathematics anxiety. This contrasts with prior findings that more teachers reduce anxiety by improving support (Yıldırım, 2012). In East Asia, however, a higher proportion of math teachers may reflect intensified instruction (Biggs, 1994), increasing pressure. Moreover, larger teacher numbers are often correlated with larger schools, which may weaken students' sense of belonging and increase anxiety (Anderman, 2002; Štremfel et al., 2024). These findings highlight potential drawbacks of larger school environments in East Asia and may inform educational policy. Digital resource availability (DIGPREP, RATCMP1) showed initial benefits, with anxiety decreasing as availability increased from very low levels, but then increasing at higher levels. This suggests basic access might alleviate mathematics anxiety (Atoyebi & Atoyebi, 2022), but an overabundance doesn't necessarily help further and might raise anxiety (Pellas, 2024). Surprisingly, STUBEHA, an index of student behaviors undermining school climate, showed a negative association with anxiety. This may be due to two factors. First, STUBEHA scores are generally low across East Asian schools (OECD, 2023a), and the behaviors it reflects (e.g., truancy, alcohol use) are considered serious and often subject to intervention (Chen et al., 2023). Second, students exhibiting such behaviors may have lower educational aspirations and thus feel less anxiety (Hessen & Kuncel, 2022). MATHEXC revealed a stepwise pattern. Schools offering differentiated courses (remedial, enrichment, or both) were linked to higher anxiety than those offering no or non-differentiated courses. This may be due to labeling effects or perceived pressure within ability grouping systems (Belfi et al., 2012; Lee, 2009).

5.4. Limitations and future research

Several limitations should be noted. First, due to high rates of missing data in the parent questionnaire, family-level factors were not included, although prior research has identified parental influences on students' anxiety (Soni & Kumari, 2017). Second, this was a predictive study and did not establish causality. The relationships identified are correlational, although partial dependence analysis helps isolate average effects. Future research may explore causal relationships between predictors and mathematics anxiety using methods such as Directed Acyclic Graphs. Third, although the six East Asian regions share a Confucian heritage, cultural practices vary due to differences in history, politics, and institutions (Tu, 1996). Therefore, more region-specific studies are warranted.

CRediT authorship contribution statement

Xu Wei: Writing – original draft, Methodology, Formal analysis. **Kan Guo:** Writing – review & editing, Validation, Supervision.

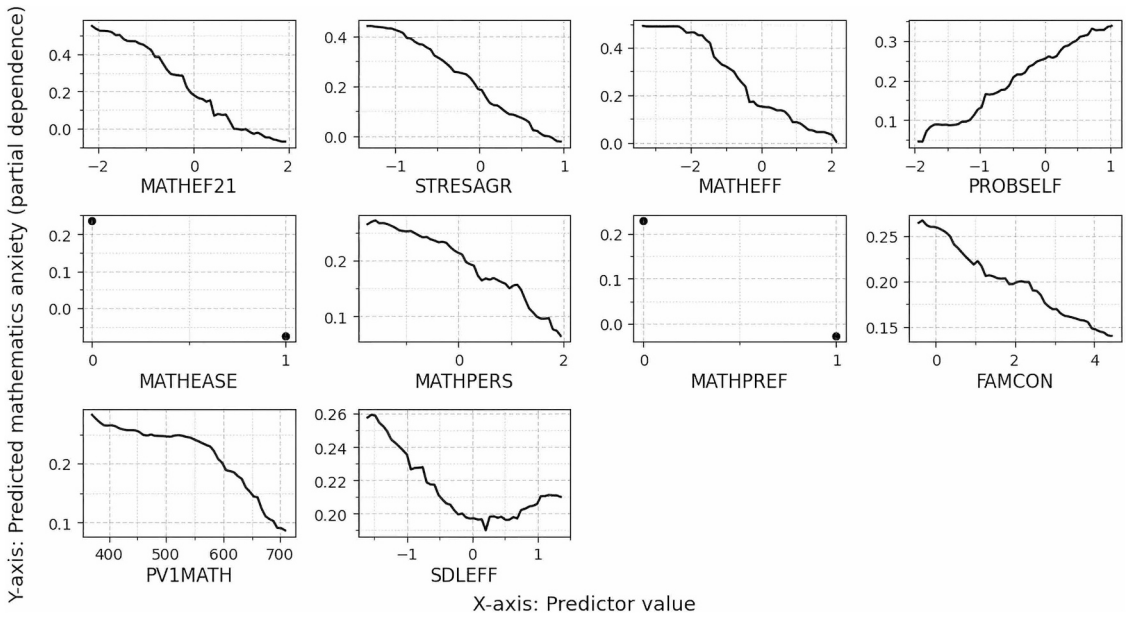


Fig. 4. PDPs at student level.

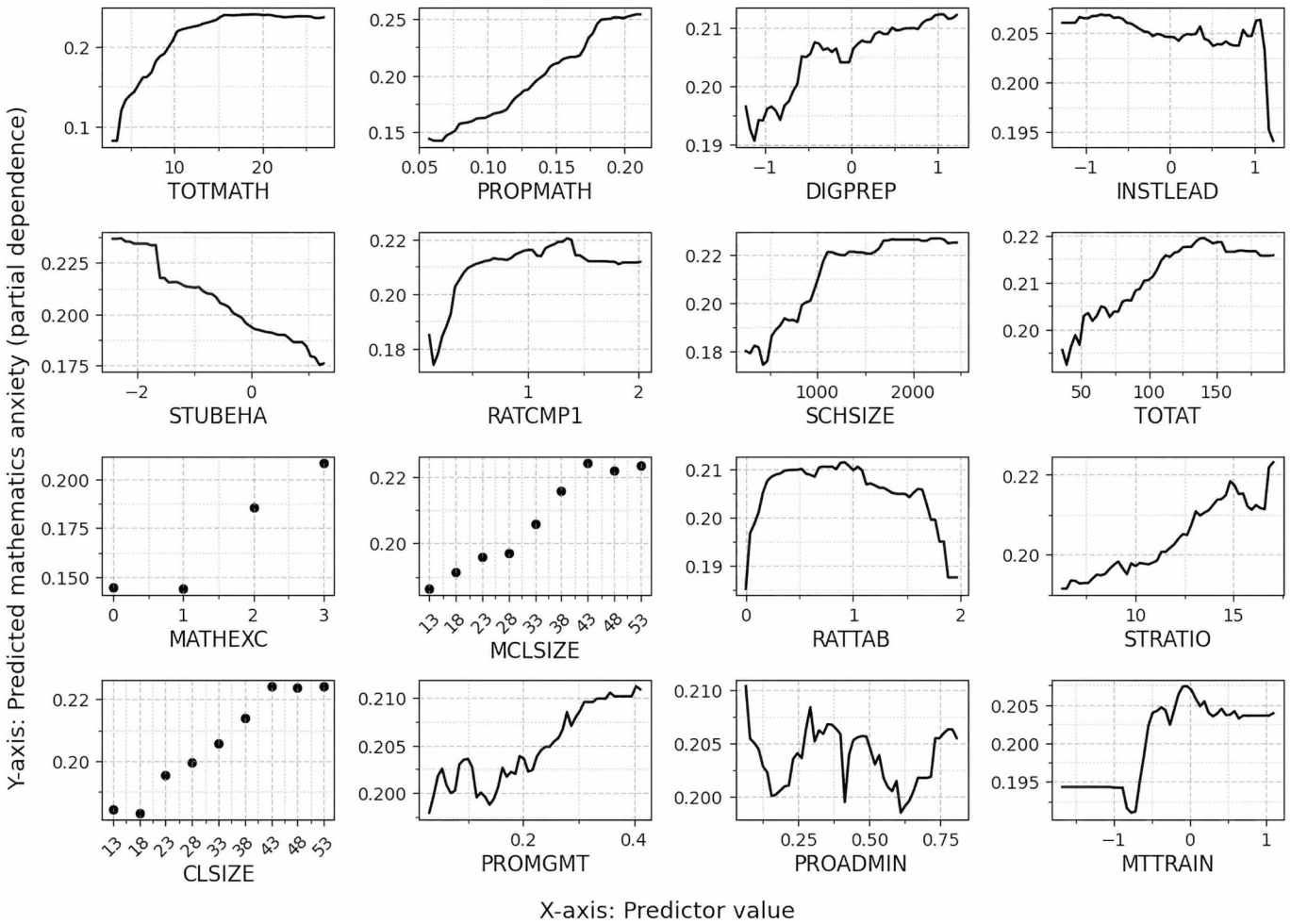


Fig. 5. PDPs at school level.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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None.

Data availability

Data will be made available on request.

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