PRIMARY STUDENTS' MATHEMATICS RELATED COSTS

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Cost is a dimension of math motivation reflecting the effort and resources associated with learning mathematics, making it an important part of students' motivation and learning experience. This study aimed to clarify the factors associated with cost by applying regression tree analysis to a data consisting of 1579 elementary students and their parents. The regression tree was trained first with a smaller dataset and then evaluated on a larger independent dataset. The analysis revealed that students perceived competence was the most prominent factor, with lower perceived competence linked to higher cost values. Mathematics performance and parental expectations further differentiated subgroups, while school-based remedial teaching and extracurricular activities explained variation in smaller branches.

INTRODUCTION

Students' motivation to study mathematics is a complex and dynamic construct that is situated within their learning and living environment. The competence they perceive and the costs they experience when engaging in mathematics learning are prominent components of their mathematics motivation and thus affect their learning outcomes (Eccles & Wigfield, 2020). Especially during the primary school years, parents and teachers play a significant role in shaping students' motivation for mathematics (Nuutila et al., 2018; Vinni-Laakso et al., 2025). Parents and teachers may aim to improve children's mathematics motivation and learning by offering support at home and remedial instruction in school. However, we do not know how these practices reduce the costs the students experience when studying mathematics. Thus, this study utilizes regression tree analysis to explore patterns in how home and school context factors and students' perceived competence and mathematics performance relate to their experienced costs across different levels and whether the identified structure is stable in a larger independent dataset.

THEORETICAL BACKGROUND

Situated Expectancy–Value Theory (SEVT) conceptualises students' motivation as a combination of their expectations of success and the values they attach to tasks, both of which are shaped by prior experiences and socio-cultural influences (Wigfield & Eccles, 2020, 2024). Within SEVT, cost is a prominent task value often referred to as the negative aspect associated with engaging in a learning activity, such as invested time, effort, or emotional strain (Eccles & Wigfield, 2020). Recent research shows that the cost, as a distinct motivational component, has unique, longitudinal implications for students' engagement and self-concept in primary school, with higher perceived

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cost linked to lower motivation and task engagement (Vinni-Laakso et al., 2025). Even though the success expectancy is one of the strongest predictors of mathematics performance, high perceived competence may not be sufficient to sustain motivation if the perceived cost of participation is high (Wigfield & Cambria, 2010).

Both home and school contexts are important socializers and arenas where success expectancies and task values develop (Nuutila et al., 2018). Social messages from parents and teachers influence, which tasks are seen as worthwhile or burdensome, particularly in relation to students' social identity (Eccles & Wigfield, 2020). Parents' child-specific beliefs, such as perceptions of ability and expectations of success, are powerful predictors of children's academic motivation and achievement even after accounting for independent indicators of ability (e.g., standardised test scores) and demographic factors (Simpkins et al., 2015). In the STEM domain, parents' expectations and messages function as some of central socialising drivers shaping students' achievement beliefs (Šimunović & Babarović, 2020). Although SEVT would imply that these parental beliefs could also influence children's perceived cost (e.g., effort, stress, opportunity loss), direct empirical evidence on this cost link — especially in primary-school mathematics — remains limited and has not yet been systematically tested.

Remedial teaching in mathematics has been shown to support both performance and motivation in primary school. A recent meta-analysis of 286 mathematics intervention studies found that programs incorporating remedial components consistently produced positive effects on students' mathematical proficiency and motivational outcomes, such as increased confidence and engagement (Rojo et al., 2024). Also, extracurricular activities such as after-school mathematics clubs have been shown to improve students' academic performance and foster positive relationships with mathematics (Brodie, 2022). Participation in hands-on, inquiry-based math clubs can reduce anxiety, increase engagement, and have positive shifts in mathematics identity among primary-school students (Virden et al., 2023). However, the field lacks research on the impact of remedial teaching or extracurricular activities on the students' perceived costs.

RESEARCH QUESTIONS

The present study aims to explore how students differ across varying levels of perceived cost in mathematics using a regression tree analysis. The research questions were:

1. How do parents' educational expectations, attending to remedial teaching or extracurricular activities at school or private, and students perceived competence and mathematics performance emerge and contribute across different levels of students cost experience?
2. How does the regression tree structure, including the relative importance of predictors compare in a larger independent dataset?

METHODS

Participants

This study utilized the data collected as a part of international longitudinal research project investigating the development of mathematics motivation in primary education: *Co-constructing mathematics motivation in primary education*—A longitudinal study in six European countries (MATHMot), funded by the Research Council of Norway (grant number 301033). The present sample consists of data from 1579 4th and 5th grade students and their parents, collected from 51 schools located in the Southern Finland in the spring of 2022 and 2023.The student data was collected during regular school days by trained research assistants.

Measures

The cost and perceived competence (PC) were evaluated among the five dimensions of the Expectancy-Value Scale (EVS; Peixoto et al., 2023), a tool that measures various facets of students' motivation in mathematics according to SEVT. Both PC and cost were measured with five items using a 4-point Likert scale (cost: Learning math requires too much of my time; PC: Math is easy for me). Cost served as a continuous root variable in the analysis. The mathematics test scores (Math) were based on a test consisting of 14 questions. The tasks were retrieved from the released items of the Trends in International Mathematics and Science Study 2011 (approval IEA 22-2022) and assessed to correspond with the project's participating countries across all grades involved. Linkage items and IRT modelling allowed the test to be put on the same scale. For each correct answer, the students received 1 point.

The parents were asked to fill out a questionnaire, and their answers were connected to their children using linkage codes. Parents' expectations regarding the child's future education level (EduEx) were assessed with an open-ended question: "How far do you expect your child to progress in their studies (e.g., No expectations, upper secondary school, university, doctoral). The responses were coded into ordinal values (0:5) that were included in the model as a categorical variable. In addition, we added four binary variables based on parents' reports whether the student had attended extracurricular activities to excel (ST1 & PR1) or remedial teaching to keep up with others (ST2 & PR2) either at school or through private tutoring.

Analytical approach

The analysis was conducted from an exploratory and descriptive perspective to identify non-linear relationships and interactions among cost-related factors. Regression tree analysis provides a data-driven way to identify combinations of academic, motivational, and contextual variables associated with varying levels of students' experienced cost (Breiman et al., 1984).

Classification and Regression Trees (CART) (Breiman et al., 1984) is a nonparametric statistical method applicable to both classification and regression problems. When the response variable is categorical, CART produces a classification tree, and when it is

continuous, it produces a regression tree. Regression trees are constructed using a binary splitting procedure, where at each node the algorithm selects the variable and split point that minimises prediction error, typically measured by the residual sum of squares (RSS). Each terminal node predicts the mean response of observations within that node. CART grows the tree to its maximal size and then applies post-pruning to control overfitting, trimming the tree to an optimal size determined by cross-validation (Breiman et al., 1984; Loh, 2014). A key advantage of CART is its ability to model complex, nonlinear relationships.

We first conducted ANOVA-based regression tree analysis with R version 4.4.1 (R Core Team, 2025) and using *rpart* package (Therneau & Atkinson, 2025) using a training sample (n = 283). The tree was pruned using the 0.5-SE rule based on cross-validation error to balance the models' complexity and predictive accuracy (Breiman et al., 1984). The 0.5-SE rule selects the simplest tree whose cross-validation error is within half a standard error of the minimum error, thereby reducing overfitting while maintaining good predictive performance. Compared to the 1-SE rule, it retains slightly more complexity, while avoiding overfitting and preserving meaningful splits. The pruned regression tree was then evaluated on an independent validation sample (n = 1296) that was not used during the training phase. This external validation aimed to assess the generalizability of the tree structure and performance. The training sample (n = 283) and the independent validation sample (n = 1296) sum up to the total number of participants (N = 1579). The model was evaluated using R^2, root mean squared error (RMSE) and mean absolute error (MAE). The tree structure and splitting rules were kept fixed, and no further moderations were added, ensuring an unbiased assessment of out-of-sample performance. To evaluate the robustness of variable importance, we compared rankings using Spearman's rank correlation and assessed overlap of the top predictors with Jaccard index.

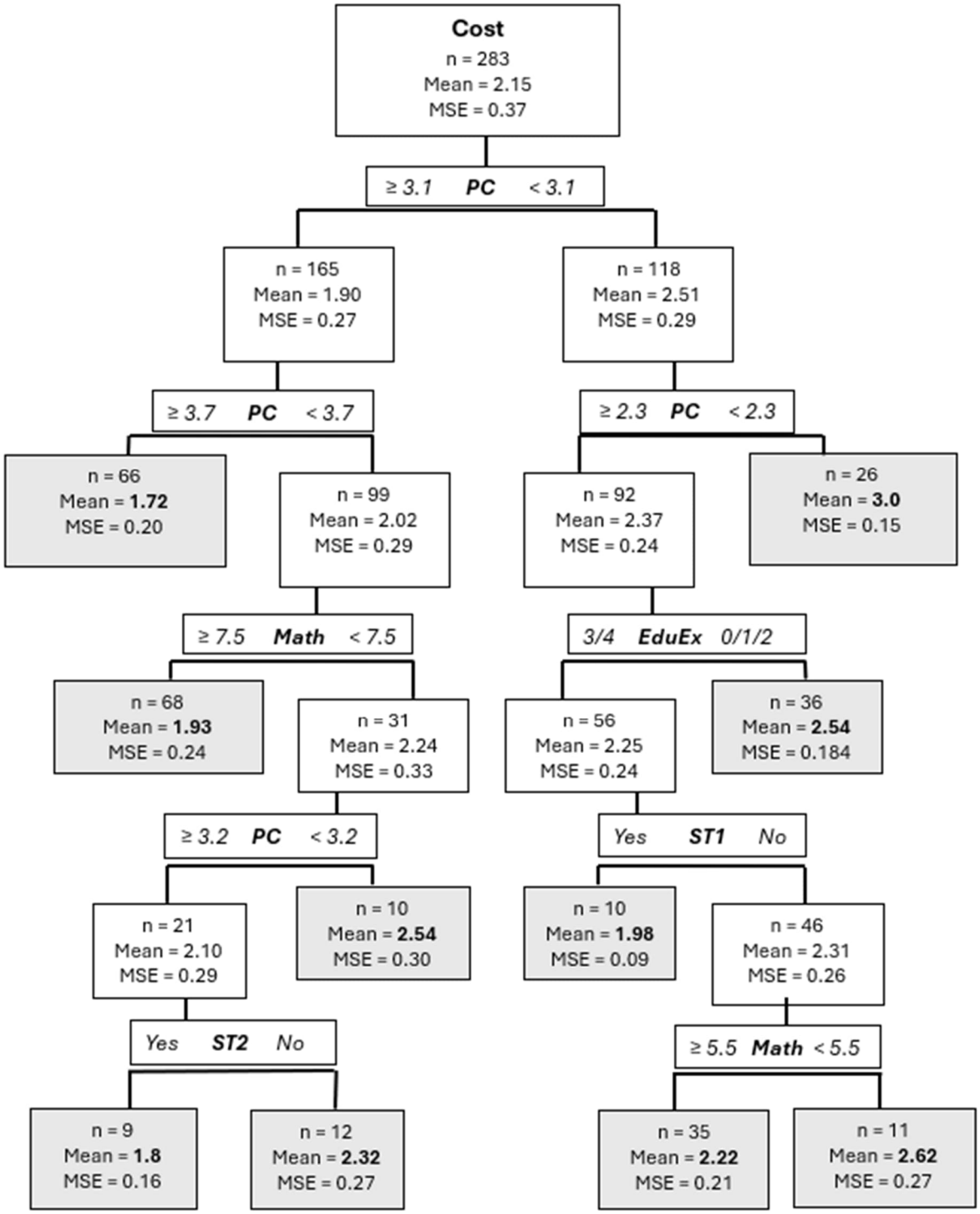
RESULTS

The pruned regression tree model contained 10 terminal nodes and a maximum depth of 5. Figure 1. presents the tree structure describing how students differ across levels of experienced costs in mathematics.

The first and most influential split was based on perceived competence (PC), the higher PC (referred to as the higher PC branch) associating with the lower cost and the lower PC (referred to as the lower PC branch) with the higher cost.

Among the higher-PC students' branch, the lowest cost value was connected to a very high PC. A similar connection was observed with the students with the lowest PC. For the moderate cost levels, further split was based on the math performance (Math), where the higher scores were linked to lower costs and vice versa. Within the lower math performance node, the differentiation was linked back to PC. The students who had higher PC and had attended in school-based remedial teaching, showed lower cost, whereas those with lower PC and no remedial teaching was connected to higher cost.

Figure 1: Regression tree model of the training sample



Note: Mean = root variable mean / MSE = mean squared error /PC = perceived competence / Math = Math test score / EduEx = Parents educational expectations / ST1 = Attending to remedial teaching at school ST2 = Attending to extracurricular activities in school.

On the lower PC branch parents' lower educational expectations (EduEx) led to higher costs. Parents' higher EduEx was associated with lower cost, especially among students who had attended in school-based extracurricular activities to excel. Among students

who had not attended in extracurricular activities, lower math performance was associated with higher costs and vice versa.

Table 1. represents the variable importance of the regression tree model. Perceived competence was the dominant predictor, accounting for 60% of the total importance. Mathematics performance was the second most important (15%), followed by attendance to school-based remedial teaching and parents' educational expectations and attendance to school-based extracurricular activities. The remaining two variables had a relatively small contribution in all.

Table 1: Variable importance

Predictor	*PC*	*Math*	*ST2*	*EduEx*	*ST1*	*PRT2*	*PRT1*
Importance	60%	15%	10%	6%	5%	2%	2%

Note: PC = perceived competence / Math = Math test score / EduEx = Parents educational expectations / ST1 = Attending to remedial teaching at school ST2 = Attending to extracurricular activities in school.

While assessing the performance of the regression tree model with the training sample (*n = 283*), the model explained 43.6% of the variance ($R^2 = 0.436$), indicating that it captured a meaningful portion of cost variability. The error metrics were moderate (RMSE = 0.456; MAE = 0.366). To evaluate the model structure and generalizability, it was assessed with an independent dataset (*n = 1296*), where it maintained reasonable generalizability, with $R^2 = 0.337$ and slightly higher error values (RMSE = 0.525; MAE = 0.417). This result indicates that the model provides a useful structure without severe overfitting. The comparison of the variable importance revealed a high rank-order consistency (Spearman's $\rho = 0.87$), indicating that the relative importance of predictors remained largely similar. Furthermore, the top three predictors were identical in both datasets (Jaccard index = 1.00).

DISCUSSION

Perceived competence emerged as the strongest predictor, dominating the overall structure of the tree, supporting findings that recognize perceived competence as one of the central drivers of motivational processes (Cf. Eccles & Wigfield, 2020). A positive finding was, that the extra teaching programmes provided in school, both remedial teaching and extracurricular activities were consistently associated with lower perceived cost. One possible explanation is that these activities enhance students' perceived competence (e.g. Rojo et al., 2024), which in turn reduces their experience of cost. Fostering students' perceived competence through individual remedial support or enrichment may mediate the relationship between an increased workload and lower costs.

Higher parental expectations on students' educational paths are linked to lower student costs. This might be influenced by the student's socio-economic background, which is known to be associated with mathematics learning and motivation, as parents who

prioritise education and have higher qualifications, may implicitly expect their children to share these values, thereby boosting their learning and motivation (Peixoto et al., 2024). Nonetheless, schools should ensure all students have access to quality learning and motivation, and work to reduce disparities caused by socio-economic differences. It remains unclear whether this dynamic is driven by parental monitoring, reinforcement of students' perceived competence, or a combination of factors, and how teachers can support the children who do not benefit from this parental influence. Further research is necessary to clarify these issues.

The regression tree analysis works as a valuable method in observing non-linear associations that shape students' math-related costs. Although the model generalized well to an independent dataset, its explanatory power remained moderate. This could indicate that while the tree is able to capture meaningful patterns related to cost, it is not able to fully capture the variation in it. The results should be interpreted as an opening that future studies can elaborate further by exploring more flexible models or adding additional predictors.

References

Breiman, L., Friedman, J.H., Olshen, R.A. & Stone, C.J. (1984). *Classification and Regression Trees*. Belmont: Wadsworth.

Brodie, K. (2022). Learning mathematics in an after-school mathematics club. *African Journal of Research in Mathematics, Science and Technology Education*, 26(3), 237–247. https://doi.org/10.1080/18117295.2022.2131267

Eccles, J. S., & Wigfield, A. (2020). From expectancy-value theory to situated expectancy-value theory: A developmental, social cognitive, and sociocultural perspective on motivation. *Contemporary Educational Psychology*, 61, 101859. https://doi.org/10.1016/j.cedpsych.2020.101859

Eccles, J. S., & Wigfield, A. (2024). The development, testing, and refinement of Eccles, Wigfield, and colleagues' situated expectancy-value model of achievement performance and choice. *Educational Psychology Review*, 36(2), 51. https://doi.org/10.1007/s10648-024-09888-9

Loh, W.-Y. (2014). Fifty Years of Classification and Regression Trees. *International Statistical Review*, 82(3), 329–348. https://doi.org/10.1111/insr.12016

Nuutila, K., Tuominen, H., Tapola, A., Vainikainen, M.-P., & Niemivirta, M. (2018). Consistency, longitudinal stability, and predictions of elementary school students' task interest, success expectancy, and performance in mathematics. *Learning and Instruction*, 56, 73–83. https://doi.org/10.1016/j.learninstruc.2018.04.003

Peixoto, F., Radišić, J., Krstić, K., Hansen, K.Y., Laine, A., Baucal, A., Sõrmus, M. & Mata, L. (2023). Contribution to the validation of the Expectancy-Value Scale for primary school students. *Journal of Psychoeducational Assessment*, *41*(3), 343–350. https://doi.org/10.1177/07342829221144868

Peixoto, F., Mata, L., Campos, M., Caetano, T., Radišić, J., & Niemivirta, M. (2024). 'Am I to blame because my child is not motivated to do math?': Relationships between parents'

attitudes, beliefs and practices towards mathematics and students' mathematics motivation and achievement. *European Journal of Psychology of Education*, 39(2), 1561–1586. https://doi.org/10.1007/s10212-023-00774-6

R Core Team. (2025). *R: A language and environment for statistical computing* (Version 4.5.2) [Computer software]. R Foundation for Statistical Computing, Vienna, Austria. https://www.R-project.org/

Rojo, M., Gersib, J., Powell, S. R., Shen, Z., King, S. G., Akther, S. S., Arsenault, T. L., Bos, S. E., Lariviere, D. O., & Lin, X. (2024). A meta-analysis of mathematics interventions: Examining the impacts of intervention characteristics. *Educational Psychology Review*, 36, Article 9. https://doi.org/10.1007/s10648-023-09843-0

Simpkins, S. D., Fredricks, J., & Eccles, J. S. (2015). Families, schools, and developing achievement-related motivations and engagement. In J. E. Grusec & P. D. Hastings (Eds.), *Handbook of socialization: Theory and research* (2nd ed., pp. 614–636). New York: Guilford Press.

Šimunović, M., & Babarović, T. (2020). The role of parents' beliefs in students' motivation, achievement, and choices in the STEM domain: A review and directions for future research. *Social Psychology of Education*, 23, 701–719. https://doi.org/10.1007/s11218-020-09555-1

Therneau, T. & Atkinson, B. (2025). *rpart: Recursive Partitioning and Regression Trees*. R package version 4.1.24, https://doi.org/10.32614/CRAN.package.rpart.

Vinni-Laakso, J., Hietajärvi, L., Juuti, K., Loukomies, A., & Salmela-Aro, K. (2025). Within-person dynamics of science self-concept, intrinsic value, and cost in elementary school: a six-year longitudinal study. *Educational Psychology*, 45(5), 561–580. https://doi.org/10.1080/01443410.2025.2489109

Virden, C., Dean, L., & Bondurant, L. (2023). The impact of after-school math club on elementary student math anxiety. *Journal of Math Circles*, 3(1), Article 2

Wigfield, A., & Cambria, J. (2010). Students' achievement values, goal orientations, and interest: Definitions, development, and relations to achievement outcomes. *Developmental review*, *30*(1), 1–35. https://doi.org/10.1016/j.dr.2009.12.001