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Student Profiles of Own Perceptions Regarding Teaching Practices and Learning Opportunities

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This study aims to define students' profiles of their perceptions in terms of teaching practices and learning opportunities and to assess the generalizability of these profiles across gender groups by using single-group and multi-group latent profile analyses. This study used Turkish national data from the PISA 2022 study (N= 7155 students from 196 schools). For female and male students, three student profiles that differed in terms of their perceptions of cognitive activation in mathematics (COGACRCO, COGACMCO) have emerged. For both groups, while Profile-1 is a profile with the lowest mean scores in all indicators, Profile-3 has the highest mean scores in all indicators. Students who are members of Profile-2, the most common profile observed in both subgroups, have scores around the average for all indicators. Results revealed that data supported partial structural similarity. Profile-1 and Profile-2 were similar in terms of all indicators. However, members of Profile-3 were found to be different between subgroups in terms of their perceptions of the learning opportunities they have for developing mathematical reasoning and mathematical thinking skills. Evidence for both predictive and explanatory similarity was obtained, which indicated that the relationships between profile memberships and both predictors and outcomes are similar across gender groups.

Introduction

Mathematical literacy refers to individuals' ability to formulate, employ, and interpret mathematics in real-life contexts by using mathematical concepts, procedures, and tools, and is regarded as a core component of 21st-century skills that supports students' higher-order thinking and problem-solving abilities when integrated into teaching and learning processes (OECD, 2013; Voogt & Roblin, 2012). The Programme for International Student Assessment

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(PISA) enables the monitoring of mathematical literacy at national and international levels and contributes to understanding the instructional conditions and student groups in which this competency is most effectively supported (Kabael & Barak, 2016). Within this framework, learning opportunities have been widely employed to explain educational inequalities and differences in student achievement across education systems.

Teaching Practices and Learning Opportunities

Learning opportunities refer to students' access to meaningful engagement with grade-appropriate instructional content and constitute a foundational concept for explaining differences in academic performance (Stevens, 1993; Wijaya et al., 2018). Over time, this concept has expanded beyond the amount of content delivered to include how instructional practices are enacted in classrooms and how they generate differentiated learning experiences for diverse student groups (Wilson et al., 2016). Research based on PISA data indicates that learning opportunities have both direct and indirect effects on mathematics achievement and mathematical literacy through individual-level variables such as mathematics self-efficacy (Carnoy et al., 2016; Santibañez & Fagioli, 2016; Wang et al., 2022; Wang et al., 2024) and play a critical role in fostering students' mathematical literacy skills (Hwang & Ham, 2021).

In the PISA 2022 cycle, learning opportunities are conceptualized as a construct related to students' mathematical reasoning skills and measured through domain-specific indicators capturing students' exposure to mathematical content and familiarity with mathematical concepts (OECD, 2023a). Exposure to formal mathematics has been identified as a key indicator of learning opportunities, showing linear or quadratic relationships with mathematical literacy across countries (Schmidt et al., 2014).

Within the PISA 2022 framework, learning opportunities are examined in close connection with teaching practices, which are analyzed along the dimensions of cognitive activation, disciplinary climate, and teacher behaviors in mathematics classrooms (OECD, 2023a). Cognitive activation, in particular, integrates teachers' selection and implementation of mathematical tasks to foster students' mathematical thinking and reasoning (Förtsch et al., 2017; Sigurjónsson et al., 2022) and has consistently been shown to have significant positive effects on students' mathematical literacy (Genç & Çolakoğlu, 2021; Kitsantas et al., 2021; Lazarides & Buchholz, 2019).

The effective provision of learning opportunities is also related to classroom organization and teacher–student interactions. Disciplinary climate, defined by the level of disruptive behaviors and the norms ensuring students' social, emotional, and physical safety (OECD, 2023a; Barr, 2016), is positively associated with mathematics performance (Sortkær & Reimer, 2018), with learning opportunities mediating this relationship (Wang et al., 2022). In addition, teacher support shapes how learning opportunities are perceived and utilized, contributing to positive attitudes toward mathematics (Lourdes et al., 2014), reduced mathematics anxiety (Li et al., 2021), and the development of mathematical literacy skills (Haara et al., 2017); meta-analytic evidence indicates statistically significant associations between perceived teacher support and academic achievement (Tao et al., 2022).

Finally, the Proactive Mathematics Learning Behavior scale in PISA 2022 captures how learning opportunities and teaching practices are reflected in students' academic behaviors, focusing on effort and perseverance in mathematics-related tasks (OECD, 2023a). Prior research indicates that enjoyment of mathematics is associated with greater effort, whereas mathematics anxiety negatively affects motivation and perseverance (Ashcraft & Krause, 2007;

García et al., 2016).

Mathematics Education in the Turkish Context

Mathematics education in Türkiye aims to develop students' mathematical thinking, problem-solving, and analytical skills, as well as their application in everyday life contexts. Curricula developed by the Ministry of National Education (MoNE) emphasize conceptual learning and practice-oriented tasks connected to real-life situations (MoNE, 2018). Nevertheless, national and international assessment results indicate that mathematics achievement in Türkiye has not yet reached the desired level, highlighting the need for improvements in instructional processes and learning opportunities (Bayram, 2024).

An examination of Türkiye's PISA results shows a steady improvement in mathematics performance over the past decade. In PISA 2022, Türkiye performed below the OECD average in mathematical literacy. The finding that 55% of the variance in mathematics performance is explained by differences between schools (MoNE, 2024a) highlights the decisive role of school-level factors and instructional processes. This proportion is substantially higher than the OECD average. Furthermore, the limited explanatory power of socioeconomic differences suggests that disparities in mathematical literacy may be largely attributable to within-school instructional processes and students' experiences (MoNE, 2024a).

This pattern reinforces the need for person-centered analyses focusing on students' perceptions of teaching practices and learning opportunities in Türkiye.

Gender Differences in Teaching Practices and Learning Opportunities in Mathematics

OECD reports emphasize that gender differences in mathematical literacy cannot be explained solely by differences in average performance levels and should be examined together with students' access to learning opportunities, classroom instructional experiences, and individual characteristics such as mathematics self-efficacy, self-concept, and anxiety. Evidence from most countries indicates that girls' and boys' average mathematics performance levels are largely comparable, whereas their perceptions of teaching practices, cognitively activating teacher behaviors, and classroom interactions may differ by gender (OECD, 2015). In the Turkish context, girls and boys demonstrate largely similar average levels of mathematics performance; however, the proportion of high-performing students tends to be higher among boys (MoNE, 2024a).

The literature suggests that students' perceptions of teacher behaviors and classroom interactions vary by gender. Instructional practices such as cognitive activation, classroom participation, and encouragement of mathematical thinking may be experienced differently by girls and boys in mathematics lessons (Eccles, 2011; Gherasim et al., 2013; Samuelsson & Samuelsson, 2016; Sigurjónsson et al., 2022; Smith & Glynn, 1990). These perceptual differences may influence how teaching practices are transformed into learning opportunities and the extent to which students benefit from these opportunities.

Within this framework, gender in the present study is not used to make a simple comparison of mathematical literacy levels between girls and boys. Instead, it is examined to investigate whether latent student profiles—defined based on perceptions of teaching practices and learning opportunities—are structurally similar for female and male students. This approach contributes to a more comprehensive understanding of how instructional processes in mathematics are organized and experienced by different student groups.

Person-Centered Approaches in Mathematics Education Research

Person-centered approaches aim to classify individuals into distinct subgroups that share similar characteristics (Muthén & Muthén, 2000). Given the heterogeneity of populations in the behavioral sciences, such approaches are essential for identifying unobserved heterogeneity (Hofmans et al., 2020). Among these, Latent Profile Analysis (LPA) is considered a flexible and powerful method for uncovering latent subpopulations (Morin et al., 2016).

Person-centered approaches such as LPA enhance the understanding of mathematical literacy by identifying latent subgroups based on patterns among mathematical literacy, student characteristics, and instructional process–related factors. Prior research using person-centered methods has identified student profiles based on mathematical modeling competency (Jeong et al., 2023), attitudes toward mathematics (Berger et al., 2020), and perceptions of mathematics teacher support and student-centered instruction (Lazarides et al., 2022).

Studies drawing on international large-scale assessments have also conceptualized learning opportunities through alternative contexts, including information and communication technology (ICT) use (Heinrich et al., 2019; Van den Beemt & Diepstraten, 2016) and educational resources at home (Liu & Whitford, 2011; Depren & Kalkan, 2017), to define student profiles. Other studies have constructed profiles using multiple variables and demonstrated differences in mathematics achievement across profiles (Xiao & Sun, 2021; Zhang & Lian, 2024). However, to the best of the authors' knowledge, no study has defined student profiles within the PISA conceptual framework based on students' perceptions of exposure to mathematical content and mathematics teachers' instructional behaviors related to teaching practices and learning opportunities.

The Present Study

Despite substantial theoretical and empirical literature documenting the effects of teaching practices and learning opportunities on students' mathematical literacy and academic performance, few studies have jointly examined these factors within the PISA conceptual framework based on students' perceptions, identified student profiles using person-centered approaches, and investigated their links with mathematical literacy. Most existing research has relied on variable-centered approaches focusing on associations among teaching practices and learning opportunities; however, such approaches may be insufficient for capturing heterogeneous patterns in students' instructional experiences.

From this perspective, jointly considering students' perceived exposure to mathematical content and their perceptions of mathematics teachers' instructional practices may provide a more holistic understanding of mathematical literacy. Moreover, examining whether these profiles are similar across student groups, particularly by gender, is important for establishing the validity of person-centered approaches in educational research.

The primary purpose of this study is to identify student profiles based on students' perceptions of teaching practices and learning opportunities—including cognitive activation in mathematics (encouraging reasoning), cognitive activation in mathematics (encouraging mathematical thinking), exposure to formal and applied mathematics tasks, exposure to mathematical reasoning and 21st-century mathematics tasks, and subjective familiarity with mathematical concepts—and to evaluate the similarity of these profiles across female and male students. In addition, the study examines the relationships between profile membership and predictor variables (students' proactive mathematics learning behaviors and their perceptions of disciplinary climate and mathematics teacher support), as well as mathematical literacy as the outcome variable. Based on the general aim of the research, the following research questions were addressed:

(1) Based on the participants' perceptions of teaching practices and learning opportunities, what profiles emerge?
(2) Is there evidence of configural similarity across the profiles for female and male students?
(3) Is there evidence of structural similarity across the profiles for female and male students?
(4) Is there evidence of dispersion similarity across the profiles for female and male students?
(5) Is there evidence of distributional similarity across the profiles for female and male students?
(6) Is there evidence of predictive similarity across the profiles for female and male students?
(7) Is there evidence of explanatory similarity across the profiles for female and male students?
(8) Do students' mathematical literacy skills differ significantly by profile membership?

Method

Participants

This study was carried out based on PISA 2022 Turkish National data. The target population in PISA 2022 consisted of 15-year-old students attending the 7th-grade or upper-grade level in educational institutions in each country. The "two-stage stratified sample design" was used in each country in the sampling process. The Turkish national sample of the PISA-2022 study consisted of a total of 7250 students (3561 female and 3689 male students) selected from 196 schools (OECD, 2023a). In this study, students with missing data in all LPA indicators (n = 95) were not included. The participants comprised 7155 students, 3517 female students (49.1%) and 3638 male students (50.9%) from 196 schools.

Measures

In this study, the constructs of cognitive activation in mathematics: foster reasoning, cognitive activation in mathematics: encourage mathematical thinking, exposure to formal and applied mathematics tasks, exposure to mathematical reasoning and 21st-century mathematics tasks, and subjective familiarity with mathematics concepts were considered as indicators. The constructs of disciplinary climate in mathematics, mathematics teacher support, and proactive mathematics study behavior were considered predictors of profile membership. The wording of the items included in each scale is provided in the Supplementary File, and mathematical literacy was included as the outcome variable.

The PISA 2022 study collected data for these constructs using a within-construct matrix sampling design (OECD, 2023a); therefore, individual item-response data are unavailable. Accordingly, weighted likelihood estimates (WLEs) obtained through IRT scaling were used for all indicator and predictor variables (Warm, 1989), and ten plausible values were used for mathematical literacy. Information on students' national study programs (PROGN) was also obtained from the PISA 2022 national database.

Due to the matrix sampling design, factor analytic techniques and internal consistency estimates could not be applied. Therefore, validity and reliability evidence was based on the PISA 2022 Technical Report (OECD, 2023b), in which Cronbach's alpha values, item fit, model–data fit, and cross-country invariance evidence were reported. In addition, only scales meeting the required reliability and international parameter criteria were included in the international database.

Mathematical literacy was measured using plausible values generated through a multivariate latent regression model that incorporates student background variables and assessment data (OECD, 2023a). Ten plausible values were drawn for each student using multiple imputation procedures and were analyzed following OECD guidelines.

The cognitive activation scales—*cognitive activation in mathematics: foster reasoning* (COGACRCO; α = .80) and *cognitive activation in mathematics: encourage mathematical thinking* (COGACMCO; α = .90)—each consisted of nine Likert-type items assessing the frequency of teachers' instructional practices aimed at fostering mathematical reasoning and thinking. Exposure to mathematical tasks was measured using the *exposure to formal and applied mathematics tasks* scale (EXPOFA; nine items; α = .76) and the *exposure to mathematical reasoning and 21st-century mathematics tasks* scale (EXPO21ST; ten items; α = .82), capturing students' reported exposure to formal, applied, reasoning-oriented, and 21st-century mathematics tasks. *Subjective familiarity with mathematical concepts* (FAMCON) was assessed using ten Likert-type items (α = .75). The predictor variables—the *disciplinary climate in mathematics* scale (DISCLIM; seven items; α = .84), *proactive mathematics study behaviour* scale (MATHPERS; eight items; α = .77), and *mathematics teacher support* scale (TEACHSUP; four items; α = .90)—were included in the analyses. All reliability coefficients were reported for Turkish students in the PISA 2022 Technical Report (OECD, 2023a, 2023b).

Data Analyses

Preliminary Analyses

In this study, individuals with missing values in all LPA indicators (n_{female}= 44, n male= 51) were excluded from the data set before applying LPA. Detailed information for LPA indicators and predictors were presented in Table 1.

Table 1. Number and percentage of missing values for indicators and predictors

Variable	n	%
Cognitive activation in mathematics: Foster reasoning	23	0.3%
Cognitive activation in mathematics: Encourage mathematical thinking	59	0.8%
Exposure to formal and applied mathematics tasks	25	0.3%
Exposure to mathematical reasoning and 21st-century mathematics tasks	51	0.7%
Subjective familiarity with mathematics concepts	42	0.6%
Disciplinary climate in mathematics	23	0.3%
Proactive mathematics study behavior	97	1.4%
Mathematics teacher support	28	0.4%

Note: Percentages are calculated based on N = 7155.

As shown in Table 1, missing values were low for both indicators (0.3%–0.8%) and predictors

(0.3%–1.4%). Little's MCAR test yielded p values of .017 for the indicators and .021 for the predictors. Using the pre-specified significance level of $\alpha = .01$, the MCAR hypothesis was not rejected; accordingly, missing values were handled using the Expectation-Maximization (EM) algorithm. Given the low proportion of missing data and the consistency with MCAR, the use of EM imputation is considered appropriate, as EM provides unbiased parameter estimates under MCAR conditions (Little & Rubin, 2019). Therefore, for LPA indicators and predictors, missing values were imputed using the Expectation Maximization (EM) algorithm, and all subsequent analyses were carried out based on this data. Descriptive statistics, Intraclass Correlation Coefficients (ICCs), and correlations between indicators and predictors were calculated for all LPA indicators and predictors using Mplus version 7 (Muthén & Muthén, 2012).

Latent Profile Analysis

In the current study, single-level LPA was applied, and single-level models with 1 to 8 profiles were tested separately for male and female student groups. Although the research data has a hierarchical structure in which students are nested within schools, single-level LPA was applied instead of Multilevel LPA in this study for two reasons: (1) Observing that the ICC values for only one indicator among the ICCs calculated for the LPA indicators, separately for male and female student groups, were greater than .05 for both groups and (2) while the number of schools with n≤5 for the female subgroup is 16, the number of schools with n≤5 for the male subgroup is 3, and these small schools (n≤5) for male and female student groups are different from each other. However, while it is emphasized in the literature that the ICCs being greater than 0.05 indicates the necessity of multilevel analyses to avoid biased parameter estimates, it is stated that ICC values less than 0.05 indicate low variability between level-2 units for nested data structures (Muthén ve Satorra, 1995). In terms of school size, based on the results of simulation studies, Park and Yu (2018) stated that for the application of multi-level analysis, if the number of level-2 units is greater than 100, the group size at level-1 should be at least 5. Accordingly, single-level LPA was applied instead of Multilevel LPA in this study, and all LPA models were estimated by using Robust Maximum Likelihood Estimation (MLR) at Mplus version 7 (Muthén & Muthén, 2012).

Considering that students were nested within schools in the PISA sampling design, the Mplus TYPE=COMPLEX option was used to adjust standard errors for clustering at the school level (Asparouhov, 2005). Although PISA provides student-level sampling weights (W_FSTUWT), these were not applied because the focus was on latent profile structure and profile similarity rather than population-level prevalence estimates. The cluster variable was defined as the school identifier. In the LPA models, indicator means were allowed to vary across profiles, whereas indicator variances were held equal due to convergence problems when variances were freely estimated (Peugh & Fan, 2013). To reduce the risk of local maxima, 800 random start values were generated, and the best 40 solutions were retained for final optimization. The final log-likelihood value was successfully replicated, indicating a stable solution.

In this study, for model evaluation and comparison, statistical criteria and theoretical considerations were taken into account. As statistical criteria, Bayesian Information Criteria (BIC), sample-size adjusted BIC (aBIC), Akaike Information Criteria (AIC), and Consistent Akaike Information Criteria (CAIC) were used. For single-group LPA, an examination of the elbow plot drawn based on ICs also guided model selection. Besides this, the Lo-Mendell-Rubin Adjusted LRT test (adjusted LMR test) was also taken into account. For this test, a non-significant p-value indicates that the model with k-1 profiles should be chosen instead of the model with k profiles. When selecting the optimal solution with an appropriate number of profiles, average posterior probabilities (AvePP), profile separation, and entropy values were also considered (Lo, Mendell & Rubin, 2001).

Tests of Profile Similarity

In this study, a six-stage process recommended in the literature was followed to test profile similarity between gender groups (Morin et al., 2016). In this process, if there is a decrease in at least two of the AIC, BIC, aBIC, and CAIC values according to the profile similarity test in the previous stage, it is accepted that similarity is provided at that level. Firstly, configural similarity, which indicates whether the same number of profiles is specified for male and female students, was tested. In the configural similarity test, a basic model with the same number of profiles for male and female student groups was estimated, and model parameters were estimated freely. Then, based on this model, a structural similarity model with between-group equality constraints for the means of the indicators for the profile was estimated, but the model was not supported by the data. As a result of examining the confidence intervals estimated for indicator means based on the configural similarity model, Partial Structural Similarity was tested by removing the equality constraints for the indicators (COGACRCO, COGACMCO, and EXPOFA) whose means differed within the profile. Since evidence of partial structural similarity was obtained, a dispersion similarity model with group equality constraints for the variances of the indicators was estimated based on this model. Distributional similarity was then tested to assess the similarity of relative profile sizes between gender groups. Since the Distributional and Dispersion similarity models were not supported by the data, Predictive Similarity was tested based on the Partial Structural Similarity model, which is the most similar model. Based on the Partial Structural similarity model, the relationships between ‘disciplinary climate in mathematics lessons,’ ‘proactive mathematics study behavior,’ and ‘mathematics teacher support,’ and profile memberships were examined through Multinomial logistic regression.

In order to ensure that the inclusion of predictors in the model did not change the nature of the profiles, the predictive similarity model was estimated using the start values from the partial structural similarity results. First, the effects of predictors on class membership were estimated freely in each sample. Then, predictive similarity was checked by restricting equality between samples for these predictor effects. The predictive similarity was evaluated by comparing the level of fit of the two models (Morin et al., 2016). In order to assess the exploratory similarity, the ‘mathematical literacy’ was included in the predictive similarity model as an outcome. In this way, it was assessed if the associations between the profile memberships and the outcome were similar across gender groups. However, 10 plausible values are provided for Mathematical literacy in the PISA international database. In this study, in order to make analyses based on these plausible values, 10 different data sets with the same data for indicators and predictors but with a different plausible value for mathematical literacy in each data set were prepared as a file with a .dat extension. A data list (as a file with a .dat extension) containing the names of these data sets was created. This data list was used with the TYPE=IMPUTATION command under the DATA main command in the Mplus program to perform analysis based on these data sets. To test explaratory similarity, the fit of the model in which the within-profile levels of mathematical literacy were freely estimated between subgroups was compared with the fit of a model in which these levels were equally constrained between groups. In addition, mean-level differences between profiles in terms of mathematical literacy were tested using the multivariate delta method (Raykov & Marcoulidies, 2004). For this purpose, the MODEL CONSTRAINT command was used in the Mplus program (Morin et al., 2016).

Results

Descriptive statistics, correlations, and Intraclass Correlation Coefficients

Descriptive statistics for LPA indicators and predictors and ICCs for LPA indicators were calculated (see Supplementary file, Table 1). The findings indicated that these measures were approximately normally distributed. For both subgroups, among the ICCs calculated for indicators, only the ICC value calculated for FAMCON was higher than .05. The ICCs for the other indicators indicated little variability across schools for these indicators (Muthén & Satorra, 1995). The correlations calculated for the relations among LPA indicators and the predictors (see Supplementary file, Table 2) show that thesere are generally significant but at low and medium levels.

Latent profile analysis for female and male subgroups

Models with one to eight profiles were tested separately for each subgroup to determine LPA models with the optimal number of profiles for male and female subgroups. Results are given in Table 1, and the elbow plots for these LPA solutions are provided in the Supplementary file.

Table 2. Fit Criteria for LPA Models Tested in This Study

Profile Solution	LL	Free par.	AIC	BIC	aBIC	CAIC	Entropy	Adjusted LMR test (p)
	Profile solutions: Female							
1-profile	-25678.417	10	51376.834	51438.487	51406.712	51402.296	------	-------
2-profiles	-24982.851	16	49997.702	50096.347	50045.508	50038.441	0.603	0.000
3-profiles	-24575.357	22	49194.714	49330.352	49260.447	49250.73	0.804	0.000
4-profiles	-24402.896	28	48861.791	49034.421	48945.452	48933.085	0.783	0.000
5-profiles	-24236.170	34	48540.340	48749.962	48641.928	48626.91	0.825	0.197
6-profiles	-24086.508	40	48253.016	48499.631	48372.531	48354.863	0.838	0.315
7-profiles	-23952.597	46	47997.194	48280.801	48134.637	48114.318	0.836	0.109
8-profiles	-23835.463	52	47774.927	48095.526	47930.296	47907.327	0.848	0.109
	Profile solutions: Male							
1-profile	-28547.708	10	57115.417	57177.408	57145.633	57141.025	-------	-------
2-profiles	-27956.536	16	55945.071	56044.258	55993.418	55986.046	0.797	0.000
3-profiles	-27339.815	22	54723.63	54860.012	54790.107	54779.969	0.881	0.000
4-profiles	-27078.521	28	54213.042	54386.62	54297.65	54284.746	0.889	0.009
5-profiles	-26745.163	34	53558.326	53769.098	53661.063	53645.395	0.893	0.008
6-profiles	-26601.607	40	53283.214	53531.181	53404.081	53385.649	0.900	0.439
7 -profiles	-26350.545	46	52793.090	53078.252	52932.087	52910.89	0.907	0.038
8-profiles	-26193.272	52	52490.545	52812.903	52647.673	52623.709	0.915	0.002
	Cross-gender similarity							
Configural similarity	-56873.617	45	113837.233	114146.634	114003.634	113965.691	0.904	-------
Structural similarity	-56941.598	30	113943.196	114149.463	114054.13	114028.834	0.909	-------
Partial structural similarity	-56905.934	33	113877.867	114104.761	113999.894	113972.071	0.906	-------
Dispersion similarity	-57021.420	28	114099.083	114291.599	114202.621	114178.769	0.905	-------
Predictive similarity-1	-56194.221	45	112472.443	112781.843	112638.843	112606.899	0.898	-------
Predictive similarity-2	-56208.102	39	112494.205	112762.352	112638.419	112605.534	0.897	-------
Explaratory similarity-1	-129042.62	61	258207.24	258626.649	258432.805	258381.371	0.879	-------
Explaratory similarity-2	-129048.332	58	258212.663	258611.446	258427.135	258378.231	0.879	-------

Note. LL: Log-Likelihood value. Free par: number of free parameters. AIC: Akaike's Information Criterion. BIC: Bayesian Information Criterion. aBIC: Sample-size adjusted BIC. Adjusted LMRT test (p): p-value of the adjusted Lo-Mendel-Rubin likelihood-ratio test. The parameter indicates that relations between predictors and profile memberships were freely estimated across gender groups in the model "Predictive Similarity-1" and constrained as equal across gender groups in the model "Predictive Similarity-2". Outcomes were freely estimated across gender groups in the model "Explaratory Similarity-1," and levels of outcome in each profile were constrained as equal across gender groups in the model "Explaratory Similarity-2"

Model selection in mixture modeling should be based on a combination of statistical fit indices, classification quality, parsimony, and substantive interpretability Morin et al. (2011). The Adjusted LMR test supported the 4-profile solution for the female subgroup and the 5-profile solution for the male subgroup. Based on the elbow plots (see Supplementary Material), the CAIC, AIC, BIC, and ABIC values continued to decrease but showed a clear elbow at the 3-profile solution for both subgroups. For the female subgroup, the 3-profile and 4-profile solutions displayed very similar profile patterns. However, the 4-profile solution yielded a lower entropy value (0.783), indicating weaker classification accuracy. Furthermore, in the 5-profile solution for the female subgroup, one profile represented only 2.33% of the sample, suggesting a potentially unstable and less meaningful class. Similarly, for the male subgroup, the smallest profiles in the 4-profile and 5-profile solutions consisted of 2.91% and 3.24% of the subgroup, respectively. In addition, the average posterior probabilities (AvePPs) for the 3-profile solutions in both subgroups indicated better classification quality compared with the 4-profile and 5-profile solutions. Importantly, the additional profiles identified in the 4-profile and 5-profile solutions did not represent substantively distinct patterns but rather reflected minor variations of the existing profiles. Considering model parsimony, classification accuracy, and the interpretability of the profiles, the 3-profile solution was judged to provide the most theoretically meaningful and practically interpretable representation of the data. Therefore, subsequent profile similarity analyses were conducted based on the 3-profile solution.

Results of The Profile Similarity Tests

Based on the 3-profile solution, a multi-group LPA model was estimated simultaneously for gender subgroups. The structural similarity model was specified based on the configural similarity model. This model resulted in higher values for all ICs than the configural similarity model, which indicated that structural similarity was not supported. It means that, at least for some indicators, within-profile means differ across gender subgroups. Confidence intervals estimated for indicator means and variances based on the configural similarity model are presented in Table 2.

Table 3. Mean and variance estimates from the 3-Profile Configural Similarity model

		Female				Male			
Profile	**Indicator**	**Mean**	**95% Confidence Interval**	**Variance**	**95% Confidence Interval**	**Mean**	**95% Confidence Interval**	**Variance**	**95% Confidence Interval**
Profile-1	COGACRCO	-1.075	[-1.221, -0.930]	0.528	[0.408 , 0.569]	-1.284	[-1.483, -1.085]	0.736	[0.636, 0.835]
	COGACMCO	-1.287	[-1.436, -1.137]	0.374	[0.338, 0.410]	-1.571	[-1.164, -1.495]	0.333	[0.273, 0.394]
	EXPOFA	-0.358	[-0.489, -0.228]	0.906	[0.841, 0.970]	-0.312	[-0.500, -0.123]	1.203	[1.056, 1.216]
	EXPO21st	-0.651	[-0.808, -0.494]	0.892	[0.814, 0.970]	-0.579	[-0.781, -0.378]	1.164	[1.022, 1.176]
	FAMCON	0.142	[0.001, 0.282]	1.602	[1.470, 1.734]	-0.129	[-0.344, 0.086]	2.393	[2.104, 2.419]
Profile-2	COGACRCO	-0.050	[-0.102, 0.001]	0.528	[0.488, 0.569]	-0.071	[-0.107, -0.035]	0.736	[0.636, 0.835]
	COGACMCO	0.107	[0.053, 0.162]	0.374	[0.338, 0.410]	0.102	[0.066, 0.139]	0.333	[0.273, 0.394]
	EXPOFA	0.151	[0.093, 0.208]	0.906	[0.841, 0.970]	0.113	[0.071, 0.156]	1.136	[1.056, 1.216]
	EXPO21st	0.123	[0.064, 0.181]	0.892	[0.814, 0.970]	0.098	[0.058, 0.139]	1.099	[1.022, 1.176]
	FAMCON	0.628	[0.550, 0.707]	1.602	[1.470, 1.734]	0.488	[0.405, 0.571]	2.261	[2.104, 2.419]
Profile-3	COGACRCO	1.052	[0.909, 1.194]	0.528	[0.488, 0.569]	1.484	[1.310, 1.658]	0.736	[0.636, 0.835]
	COGACMCO	1.730	[1.568, 1.891]	0.374	[0.338, 0.410]	2.026	[1.927, 2.125]	0.333	[0.273, 0.394]
	EXPOFA	0.658	[0.507, 0.809]	0.906	[0.841, 0.970]	0.386	[0.183, 0.556]	1.136	[1.056, 1.216]
	EXPO21st	0.807	[0.661, 0.952]	0.892	[0.814, 0.970]	0.552	[0.348 , 0.723]	1.099	[1.022, 1.176]
	FAMCON	1.485	[1.280, 1.689]	1.602	[1.470, 1.734]	1.335	[1.090 , 1.541]	2.261	[2.104, 2.419]

All indicator means for Profile-1 and Profile-2 were similar for the two subgroups, but for the members of Profile-3, within-profile means of COGACRCO, COGACMCO, and EXPOFA differed between subgroups. Accordingly, the Partial structural similarity model in which the equality constraint for COGACRCO, COGACMCO, and EXPOFA indicators' means between gender subgroups was relaxed was estimated. Compared to the configural similarity model, this model resulted in lower BIC and aBIC values, indicating that the data supported the Partial Structural Similarity model. Dispersion similarity was assessed based on the Partial Structural Similarity model, but it was not supported by study data (Morin et al., 2016). Table 2 shows that the confidence intervals for COGACMCO indicator variances overlapped, but variances for all other indicators differed across subgroups. Then, the distributional similarity was assessed, but the data did not support this model. Accordingly, the profiles were interpreted based on the partial structural similarity model, and further analysis was carried out. Based on the Partial structural similarity model, the profiles are illustrated in Figure 1 and 2, respectively females and males.

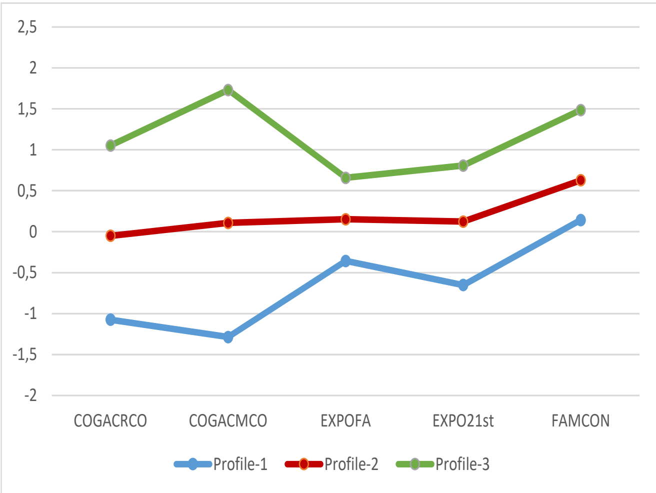

Figure 1. Final 3-profile solution for females

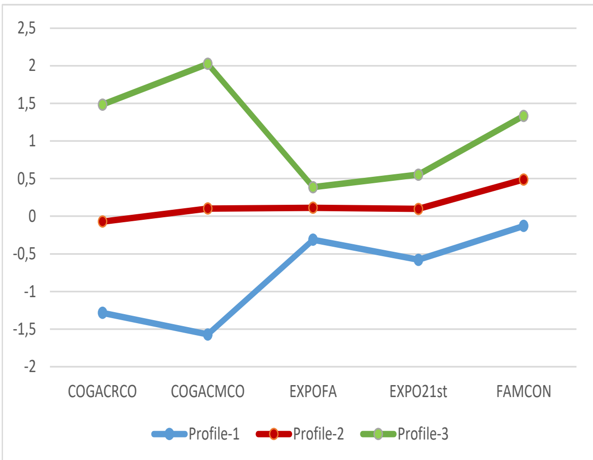

Figure 2. Final 3-profile solution for males

In both subgroups, three profiles differed substantially in terms of the means of COGACMCO and were similar in the means of EXPOFA. Students assigned to each profile were examined in terms of attendance at the national study program (see Supplementary file, Table 3).

Profile-1 had the lowest mean scores across all indicators, particularly for COGACRCO and COGACMCO. Students in this profile reported less frequent teacher practices aimed at promoting mathematical reasoning and thinking, as well as limited exposure to applied and formal mathematical tasks. They also reported infrequent exposure to tasks supporting 21st-century skills. In contrast, their perceived familiarity with mathematical concepts was slightly above average. This profile was less common among female students than among male students.

Profile-2 included students with around-average scores across all indicators in both subgroups. Their perceived familiarity with mathematical concepts was slightly above average. This was the most common profile in both subgroups.

Profile-3 had the highest mean scores across all indicators, especially for COGACMCO and COGACRCO. Students in this profile reported frequent teacher practices promoting mathematical reasoning and thinking, higher participation in activities involving evaluation and solution development, and greater exposure to tasks supporting 21st-century skills. They also reported higher familiarity with mathematical concepts and greater exposure to both applied and formal mathematical tasks than students in Profiles 1 and 2. Within this profile, the means of COGACMCO, COGACRCO, and EXPOFA differed significantly between female and male subgroups. This was the least common profile in both subgroups.

Profile-3 (the profile with the highest mean) was chosen as the reference for assessing the predictive similarity, and each profile was compared with the reference group in terms of the predictors' effects. The fact that the predictive similarity model resulted in lower BIC, aBIC, and CAIC values than the model in which the predictors' effects were freely estimated between subgroups (seen in Table 1) indicated that the predictive similarity was supported. The results of the Multinomial Logistic Regression are presented in Table 3.

Table 3 Results of the Multinomial Logistic Regression

	Profile 1 vs. Profile 3		Profile 2 vs. Profile 3	
Predictor	b (SE)	OR	b (SE)	OR
DISCLIM	-0.716** (0.088)	0.489	-0.293** (0.058)	0.746
MATHPER	-1.212** (0.108)	0.298	-0.670** (0.058)	0.512
TEACHSUP	-1.248** (0.105)	0.287	-0.517** (0.058)	0.591

**p<.01

According to the Multinomial Logistic Regression results, significant negative relationships existed between all predictors and the likelihood of being a member of Profile-1 and Profile-2 (compared to being a member of Profile 3). These findings indicated that students who had a more positive perception of the disciplinary climate in mathematics lessons and students who had a high perception of the support provided by mathematics teachers to students in lessons were significantly more likely to be members of Profile-3 (compared to being a member of Profile-2 and Profile-1). Students who reported more effort and persistence in math-related tasks were also significantly more likely to be members of Profile-3 (compared to being members of Profile-2 and Profile-1). Evidence for predictive similarity indicates that the relationships between profile membership and predictors are similar between gender subgroups.

Afterward, the Exploratory similarity model was fitted and supported by data (see Table 1). Based on the exploratory similarity model, mean-level differences were tested in terms of outcome between each profile pair, and the results are presented in Table 4.

Table 4 Means Levels of Each Profile in Terms Of Mathematical Literacy

	Profile-1	Profile-2	Profile-3	Significant Differences
Mathematical Literacy	435.149**	451.991**	473.019**	Profile-2> Profile-1
				Profile-3> Profile-1
				Profile-3> Profile-2

**p<.01

The mean levels of mathematical literacy of the students who were members of Profile-3 were significantly higher than students who were members of Profile-2 and Profile-1. Therefore, it can be concluded that the mean levels of mathematical literacy of students with high perceptions of opportunity to learn and teaching practices were higher, and the mean levels of mathematical literacy of students with lower perceptions were lower. Evidence for exploratory similarity indicates that the associations between profile membership and mathematical literacy can be generalized across gender subgroups.

Results and Discussion

This study aimed to define student profiles in terms of teaching practices and learning opportunities examined in the PISA 2022 study and to assess the generalizability of the profiles among gender groups. Rather than examining teaching practices and learning opportunities as separate variables, this study shows that different teaching practices interact to form student profiles. In this section, the findings related to the identified student profiles, their predictors, and outcomes are discussed in relation to the literature, with particular attention to gender subgroup differences.

Studies have examined student profiles using data from large-scale assessments (Berger et al., 2020; Depren & Kalkan, 2017; Jeong et al., 2023; Lazarides et al., 2022). In the current study, learning opportunities and students' access to these opportunities are conceptualized within the PISA framework (OECD, 2023a). Although no study was found that directly classifies students based on this conceptualization, related research has addressed learning opportunities through ICT use (Van den Beemt & Diepstraten, 2016) and home educational resources (Liu & Whitford, 2011). Therefore, the findings were compared with studies examining learning opportunities in different contexts. Previous research based on PISA data has consistently identified three profiles among Turkish students, including ICT use profiles (Basaran, 2024) and latent classes related to home educational resources (Depren & Kalkan, 2017). Consistent with this literature, three profiles were also identified in the present study in terms of students' perceptions of teaching practices and learning opportunities. The recurrence of three profiles across different contexts suggests that educational opportunities in Turkey vary according to student perceptions and are shaped by both school- and home-related factors. From a constructivist perspective, these profiles may reflect differences in students' capacities to construct knowledge based on the instructional environments provided by their teachers

(Jonassen, 1991). Moreover, the replication of similar profile structures across studies points to the potential role of broader socio-cultural factors, such as socio-economic status and institutional policies.

The greatest differentiation between the profiles is revealed in the cognitive activation in Mathematics. Students' perceptions of how often mathematics teachers perform behaviors that encourage mathematical thinking are very effective in the formation of the profiles. Also, the profiles differ in terms of mathematical literacy levels. Previous studies suggest that there is a significant relationship between cognitive activation and mathematical literacy (Genç & Çolakoğlu, 2021; Kitsantas et al., 2021; Lazarides & Buchholz, 2019), which is in line with the results of this study. Genç and Çolakoğlu (2021) found that cognitive activation is one of the variables explaining mathematical literacy. In the Turkish educational context, where classroom instruction tends to be teacher-directed, the prominent role of cognitive activation in distinguishing Profile-3 highlights the critical importance of how instructional authority is enacted rather than whether it exists. An additional point concerns the FAMCON indicator in Profile-1. Although students in this profile reported very low levels of cognitive activation, their familiarity with mathematical concepts was not equally low. This pattern should be interpreted cautiously, because FAMCON reflects self-reported familiarity rather than demonstrated conceptual mastery. Therefore, this finding may point to a more superficial or recognition-based familiarity with mathematical concepts that does not necessarily translate into higher-order thinking or mathematical literacy.

Another aim of the study was to examine the generalizability of the identified profiles across female and male student subgroups. The findings indicated similar indicator means for Profile-1 and Profile-2, whereas a differentiation emerged in Profile-3. Specifically, male students reported higher perceptions of teachers' practices aimed at improving reasoning skills and encouraging mathematical thinking. This finding should be interpreted cautiously, as students' perceptions of cognitive activation may not fully correspond to actual classroom practices (Sigurjónsson et al., 2022), and perceptions of the classroom environment may vary by gender (Dursun & Aksoy, 2024; Samuelsson & Samuelsson, 2016; Smith & Glynn, 1990). For example, boys have been reported to perceive themselves as more participatory in mathematical activities than girls (Samuelsson & Samuelsson, 2016). In the Turkish context, Dursun and Aksoy (2024) found that girls perceived lower levels of teacher gender-equality behaviors in mathematics lessons than boys, suggesting that mathematics classrooms may be experienced as less equitable by female students. Accordingly, the higher cognitive activation perceived by male students in Profile-3 may stem from both differences in instructional experiences and gendered interpretations of similar classroom practices. This finding highlights the importance of considering gender not merely as a demographic variable, but as a factor shaping how students experience teaching practices and learning opportunities in mathematics classrooms. It may also be linked to differences in teachers' instructional beliefs and practices (Mueller et al., 2014; Wong & Low, 2020). Since mathematical thinking is shaped by the learning environments and tasks designed by teachers (Wong & Low, 2020), variation across classrooms and schools may influence students' perceptions of cognitive activation. In this regard, the high inter-school variability reported for Turkey in PISA 2022 (MoNE, 2024a) may help explain the heterogeneity observed across student profiles.

Further analyses showed that the same number of profiles emerged for both male and female students. No differences were observed between profiles in terms of students' perceptions of exposure to formal and applied mathematical tasks. In PISA, this variable reflects not only exposure to algebra and geometry content but also opportunities to learn applied mathematics in real-life contexts (Schmidt et al., 2014). Although the OECD (2013) noted that cross-country differences may arise because 15-year-olds attend different grades and mathematics programs, this situation does not apply to Turkey. In Turkish schools, mathematics instruction is based on a centrally designed curriculum, and schools are required to use textbooks approved by the Ministry of National Education (MoNE, 2024b). Therefore, the lack of profile differences on this variable may be explained by the limited differentiation between schools in terms of students' exposure to formal and applied mathematical tasks.

No differences were observed between female and male students in Profile-1 and Profile-2. Consistent with country-level findings, prior research also reports no gender differences in perceptions of exposure to formal and applied mathematical tasks (OECD, 2015). However, unlike the existing literature, a gender-based differentiation emerged in Profile-3. Female students in this profile reported higher perceived exposure to formal and applied mathematical tasks than male students. According to the OECD (2015), such differences in perceptions may be related to changes in students' opportunities to enroll in different programs.

It was found that students who perceived a positive disciplinary climate in mathematics lessons and discipline in terms of the learning environment were more likely to be members of Profile-3. At the same time, students who stated that their teachers supported them in the lessons and provided additional help when needed were more likely to be assigned to this profile. Wang et al. (2022) also concluded that there is a relationship between disciplinary climate and OTL and that students in well-disciplined classrooms have better learning opportunities.

Finally, the profiles differ in terms of students' mathematical literacy skills. Students who were members of Profile-3 had higher mathematical literacy levels than those assigned to Profile-1 and Profile-2. Students who were members of Profile-3 stated that their teachers encouraged them to think mathematically more, provided students with sufficient support where necessary, and thus created better learning environments in mathematics lessons. Another finding was that students assigned to Profile 2 had higher mathematical literacy than students assigned to Profile 1. In support of these findings, studies show that factors that create teaching practices and learning opportunities positively affect mathematical literacy (Kaiser & Willander, 2005; Kramarski & Mizrachi, 2006).

Based on these results, practical interventions should be differentiated according to profile characteristics. For students in Profile 1, who showed the lowest levels of cognitive activation and support, priority should be given to structured scaffolding strategies, such as asking open-ended questions with prompts, breaking complex problems into manageable steps, and providing guided feedback during solution processes. For students in Profile 2, teachers should move beyond procedural instruction by using discussion-based problem-solving activities that require students to explain, compare, and justify their solutions. For students in Profile 3, whose perceptions of 21st-century skills related to mathematical tasks and reasoning are relatively lower, instruction can be enriched through real-life mathematical tasks that connect school mathematics to authentic contexts and encourage the integrated use of reasoning, communication, and problem-solving skills. Accordingly, teacher training should focus not only on general support, but also on how to design cognitively activating tasks, scaffold students' responses, and connect mathematical content to meaningful everyday situations.

These recommendations are consistent with the 2024 updated Turkish mathematics curriculum, which emphasizes a student-centered approach, teacher guidance, and the development of integrated skills such as analysis, inference, and reasoning (MoNE, 2024c).

This study has several limitations. First, the generalizability of the profiles was evaluated based on gender. In addition to gender, cross-national studies have been conducted to examine generalizability across countries (Morin et al., 2016), and future studies can be conducted this way. Secondly, student opinions were taken in the measurement tools included in the teaching practices and learning opportunities framework. In addition to student opinions, teacher opinions, or the opportunities schools provide students can be examined more in-depth with data obtained by the school administration.

Declarations

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Ethics Statements: *This study is a secondary analysis using openly available PISA 2022 data. The authors did not directly administer any interventions to human subjects.*
Conflict of Interest: *The authors declare that they have no potential conflicts of interest.*
Informed Consent: *Informed consent was not required for this study as it is based on secondary analysis of anonymized, publicly available data.*
Data availability: *The data used in this study are publicly available from the OECD PISA 2022 database (https://www.oecd.org/pisa).*

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