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SOCIOECONOMIC STATUS, DISCIPLINARY CLIMATE, AND PISA 2022 MATHEMATICS ACHIEVEMENT: A FIVE-COUNTRY MULTILEVEL STUDY WITH ROMANIAN MINORITY-STRATA EVIDENCE

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Abstract: This comparative study utilizes the PISA 2022 data from Estonia, Finland, Germany, Hungary, and Romania to consider how student socioeconomic status (SES), peer SES composition, SES inequality, and disciplinary climate –both positive and negative– align with mathematics achievement. For each country and for both Romanian- and Hungarian-language strata, hierarchical linear models were estimated. Mean peer SES and individual SES had consistent positive relationships with achievement, while SES variance did not have a significant relationship with achievement. Mean disciplinary climate was a predictor of achievement in several countries while heterogeneity (or variation) in disciplinary climate did not explain achievement variation. The strata analyses provided evidence of sharper SES-based disparities among students in the Hungarian-medium schools and more pronounced disciplinary-climate effects for children attending Romanian-medium schools. Overall, the results demonstrate greater importance of average peer contexts rather than between-school inequality in SES.

Key words: PISA 2022; multilevel modelling; socioeconomic status; peer effects; school climate

1. Introduction

Socioeconomic stratifications continue to structure educational inequality and are a significant area of empirical study. Researchers have reported a substantial association between students’ socioeconomic status (SES) and their academic performance, including mathematics achievement data on international standardized assessments (PISA; OECD, 2019, 2023, 2024; Sirin, 2005). Previous work has described SES as a multidimensional factor that can operate through a variety of mechanisms, such as material and learning resources, parental expectations, and other similar cognitively stimulating environments (Reardon, 2011). Perhaps most importantly, SES is more than just individual traits or characteristics. The socioeconomic makeup of students' schools and friend groups can positively or negatively influence students' outcomes, and these contextual factors can have a uniquely strong and independent relation to learning outcomes.

1.1 Peer Effects and Contextual SES: Beyond Mean SES Toward Peer-Exposure Models

A considerable body of research has demonstrated that the socioeconomic composition of schools - most often quantified by the mean SES of students' peers - is positively correlated to student outcomes (Lüdtke et al., 2009, Marks, 2014, Van Ewijk & Sleegers, 2010). More recently, this body of work has advanced the analysis by highlighting the possibility that socioeconomic heterogeneity among students within schools may also influence students' means of opportunity and learning environments. SES variation may have implications for the distribution of social capital, academic expectations, and peer norms (Borman & Dowling, 2010). While these notions may occur in a theoretical sense, in regular reporting of PISA results, little attention is paid to measures of SES dispersion among students within each school, either as variance or polarization.

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The current study addresses this omission; we analyze two interrelated aspects of contextual SES. The first is peer SES exposure, which we operationalize as the mean ESCS at the school level, which serves as a gauge of the SES context of students. The second is peer SES heterogeneity, which we measure as variance in ESCS within schools, which builds upon the student diversity dimension of SES. Both of these distinctions follow network-based models of peer effects, which postulates that achievement-related behaviors and norms spread through the networks created by exposure, imitation, and reinforcement (Bramoullé et al, 2009; Sacerdote, 2011).

In such theories, mean SES is the initial exposure to the peer norms that are academically supportive, while SES heterogeneity affects the possible pathways through which those norms may flow. Heterogeneity may facilitate - or restrain - peer diffusion; the degree of segmentation and clustering of networks, and distribution of relational ties, determines the possibility that all peers enact the flows of peer diffusion. Schools are not simply a collective of individual students but are quasi-network contexts where socio-economic characteristics shape students' exposure to - and flow of - academic achievement norms (Giletta et al., 2021; Tsou, 2024).

1.2 School Climate and Structural Conditions in PISA 2022

PISA 2022 has focused on measures of school climate, learning environments, and structural constraints of education systems (OECD, 2023, 2024). Research has shown that disciplinary climate is a strong non-cognitive correlate of achievement that can be as strong as or stronger than some structural aspects of education systems, such as school autonomy or leadership practices (Kraft et al., 2016). Disruption in a classroom reduces instructional time, limits teachers' capacity to provide exemplary instruction, and decreases students' engagement in learning activities (Agasisti et al., 2021). However, PISA reporting generally highlights disciplinary climate at average levels and little analysis of variability, or fragmentation, of climate within schools, all of which can represent inconsistent or fragmented rule enforcement and behavioral expectations across classrooms.

In this study, we include both the mean level of disciplinary climate, representing overall behavioral expectations, as well as within-school variance of disciplinary climate to represent fragmentation or inconsistency of behavioral norms. By analyzing both mean disciplinary climate and variance of disciplinary climate in relation to peer-SES composition and peer-SES heterogeneity, we are able to demonstrate whether peer-related mechanisms are only dependent on average exposure, or whether they arise from heterogeneity and fragmentation in students’ peer environment. This lack of analysis of variability has, to our knowledge, not been examined empirically in cross-national PISA analyses, but is highly relevant to understanding how contextual factors are linked to students' outcomes.

1.3 Education Systems in Central and Eastern Europe and Linguistic Minorities

While minority education in more recent work emphasizes analytic frameworks focused on governance, resource distribution, and the needs of a minority-language community in the Central and Eastern European context (Silova, 2010; Kiss & Toró, 2025), the Romanian case provides an interesting context to explore socio-economic and peer-composition effects where education has historically been developed along linguistic, ethnic and regional lines (Silova, 2010).

In Romania there are separate school tracks based on language of instruction (Romanian-, Hungarian-, and mixed-language), each with a distinct historical and community-specific context. Although valuable, very few analyses have systematically compared SES and peer composition, disciplinary climate, or structural school factors across Romanian and Hungarian language school strata within a PISA-based framework in Romania. Without such an analytic lens, it limits understanding of economic, contextual influences in segmented language schooling, a key feature of the educational landscape in Romania.

1.4 The Present Study

The present paper uses PISA 2022 data from Estonia, Finland, Germany, Hungary, and Romania to tackle two major questions. First, we analyze the extent to which student-level SES, peer SES, SES heterogeneity, discipline climate, and climate heterogeneity are related to mathematics achievement. Second, we analyze if SES heterogeneity and climate heterogeneity explain differences in mathematics achievement after accounting for mean peer characteristics, and whether these relationships differ between the two linguistic strata in Romania: the Romanian-language strata compared to the Hungarian-language strata. By combining network-based perspectives on the effect of peer exposure with cross-national and within-country comparisons, the current study adds to existing scholarship about educational inequalities, contextual SES and peer effects, and minority education in Central and Eastern Europe.

2. Method

2.1 Participants and Data Sources

The research utilized microdata collected during the 2022 cycle of the Programme for International Student Assessment (PISA 2022) by the Organisation for Economic Co-operation and Development (OECD). PISA uses a stratified two-stage sampling design, in which schools are randomly selected and followed by the sampling of eligible students within a school (OECD, 2024). All analyses were conducted using publicly accessible student and school-level files which contain de-identified data.

Five countries were selected to represent a contrast in socioeconomic inequality, minority education paradigms, stratification, and governance arrangements: Romania, Hungary, Finland, Germany, and Estonia. These systems represent a variety of European educational systems in the educational research literature; including Nordic comprehensive systems (Estonia, Finland); dual or tracked systems (Germany, Hungary); and linguistically differentiated, yet moderated stratified systems (Romania). Previous research has identified these cases as informative models in understanding socioeconomic gradients, peer-composition effects, and schooling for minority-language students in Central and Eastern Europe (European Commission: Directorate-General for Education, Youth, Sport and Culture, 2022; Kiss & Toró, 2025; OECD, 2023).

The sizes of analytic samples were drawn from our merged student–school dataset collected for the study. The final dataset represented 7,364 students from 262 schools in Romania; 6,198 students from 262 schools in Hungary; 10,239 students from 241 schools in Finland; 6,116 students from 257 schools in Germany; and 6,392 students from 196 schools in Estonia. Counts included nonmissing observations on mathematics plausible values (PV1–PV10) and valid school identifications.

Romanian Stratum subsamples. Due to the ethnolinguistic division of the Romanian educational system (Kiss & Toró, 2025), separate analyses were conducted for two subsamples. The Romanian-language stratum consisted of 5,933 students attending 201 schools, and the Hungarian-language stratum consisted of 1,128 students attending 34 schools in Romania. The STRATUM variable from the national sampling frame was recoded to represent the Romanian, Hungarian, and a Mixed strata. The Mixed stratum had limited clusters and produced inconsistent variance estimates and were removed from the multilevel analysis.

2.2 Measures

2.2.1 Mathematics Achievement

Mathematics proficiency was measured using PISA's ten plausible values (PV1MATH–PV10MATH), which represent uncertainty in latent proficiency estimates generated through item response theory procedures (Rubin, 1987; von Davier et al., 2009). All models were estimated separately for each plausible value, and results were combined using Rubin's multiple-imputation rules.

2.2.2 Student-Level Predictors (Level 1)

The student-level covariates comprised four variables that have been examined in previous work in PISA research: (1) socioeconomic status (ESCS), a composite index reflecting family wealth, parental education, and cultural resources; (2) gender (female = 1); (3) grade (centered), defined as the student's grade relative to the national modal grade for 15-year-olds; and (4) immigrant background, based on the OECD classification of first- and second-generation immigrant status. These indicators are strong candidates as significant sources of variation in cognitive performance (OECD, 2019, 2023; Sirin, 2005).

2.2.3 Peer Composition and Classroom Climate (School-Aggregated Level-1 Variables)

To assess peer exposure and pseudo-network processes (Lüdtke et al., 2009; Van Ewijk & Sleegers, 2010), several school-aggregated variables were constructed from student reports. These included: (1) mean ESCS, reflecting exposure to socioeconomically advantaged peers; (2) ESCS variance, capturing within-school socioeconomic heterogeneity; (3) mean disciplinary climate, based on PISA items assessing classroom disruptions and orderliness; (4) disciplinary climate variance, indicating within-school variability in perceived climate; and (5) the proportion of migrant-background students in each school. These measures correspond to contemporary peer-effects frameworks in which contextual means represent exposure to group norms, while heterogeneity indexes capture processes related to diffusion, contagion, or social comparison (Sacerdote, 2011; Willms, 2010).

2.2.4 School Structural Indicators (Level 2)

School-level predictors were obtained from the PISA school questionnaire and standardized within each country. Five indicators were included: (1) school autonomy, representing locally held decision-making and governance responsibilities; (2) school leadership, based on principals' reports of instructional and administrative leadership practices; (3) the teacher shortage index, reflecting perceived shortages of qualified instructional staff; (4) the material-resource shortage index, capturing the adequacy of instructional materials and funding; and (5) ICT resources, indicating the availability of hardware, software, and digital infrastructure. These structural features correspond to institutional conditions frequently linked to student performance in comparative education research (Agasisti et al., 2021; OECD, 2023).

2.3 Data Preparation and Analytical Strategy

2.3.1 Merging of Student and School Files

The student database and school database were merged using the *country identifier* and *school identifier* variables, and only the five selected countries were retained for analysis. Although PISA data can be analyzed using the EdSurvey R package (Zhang et al., 2024), which incorporates sampling weights and jackknife replicate methods automatically, the present study followed the modeling approach adopted in prior cross-national multilevel analyses (Lüdtke et al., 2009). All models were estimated using the *lme4* package, and sampling weights were not applied, consistent with methodological recommendations for multilevel analyses in which the primary interest lies in relationships among school- and student-level predictors rather than population-representative estimates (Rutkowski et al., 2010).

2.3.2 Missing Data Handling

Missing data were limited across predictors (generally below 3% in all countries, with the exception of ESCS in Germany). No imputation procedures were applied to the predictors. For each plausible value, the multilevel models were estimated using all available observations, relying on full-information maximum likelihood to handle missingness in the outcome.

2.3.3 Multilevel Modeling

For each country and for the Romanian subsamples, two hierarchical linear models were estimated. **Model 1** specified fixed effects for the level-1 student covariates (ESCS, gender, grade, and immigrant status) and for the school-aggregated peer and climate indicators (mean ESCS, ESCS variance, mean disciplinary climate, climate variance, and the proportion of migrant-background students). **Model 2** extended this baseline specification by incorporating level-2 structural predictors: school autonomy, school leadership, teacher shortages, material-resource shortages, and ICT resources.

All models **employed random intercepts to** account for between-school variation in mathematics performance. Random-slope specifications were not pursued, as several strata contained relatively few clusters and initial estimations produced nonconvergent or unstable variance–covariance estimates.

The general two-level model for each plausible value *k* can be written as:

$$Y_{ijk} = \beta_{0j} + \beta_1(\text{ESCS})_{ij} + \beta_2(\text{Female})_{ij} + \cdots + e_{ijk}$$

$$\beta_{0j} = \gamma_{00} + \gamma_{01}(\text{School Variables})_j + u_{0j}$$

2.3.4 Combining Estimates Across Plausible Values

Estimates across the 10 plausible values were combined using Rubin's rules (Rubin, 1987):

$$\bar{B} = \frac{1}{m}\sum_{k=1}^{m} B_k$$

$$T = \bar{U} + (1 + \frac{1}{m})B$$

where T represents the total variance used for statistical inference.

2.4 Ethical Considerations

The study relied exclusively on publicly accessible, fully anonymized secondary data from PISA 2022. Because no identifiable or sensitive personal information was processed, institutional ethical approval was not required. All analytic procedures were conducted in accordance with the OECD PISA data-use agreement and adhered to relevant national and institutional data-protection standards.

3. Results

3.1 Five-Country Multilevel Models

Multilevel models were estimated separately for Estonia, Finland, Germany, Hungary, and Romania to assess the associations of student SES, peer SES composition, disciplinary climate, and school-level structural factors with mathematics achievement. All estimates were obtained using the ten plausible values for mathematics, combined according to Rubin's rules, and weighted following OECD guidance for country-level analyses.

Fixed-Effect Estimates. Across systems, student socioeconomic status (ESCS) functioned as a positive and statistically robust predictor of mathematics achievement, consistent with prior work on socioeconomic gradients in PISA (OECD, 2023, 2024; Sirin, 2005). The magnitude of the ESCS coefficient was largest in Finland (B ≈ 34, $p < .001$) and Estonia (B ≈ 28, $p < .001$), moderate in Germany and Romania, and comparatively modest in Hungary.

Peer SES composition (mean ESCS) also yielded strong positive fixed effects in all five countries. The largest estimates were observed in Romania (B = 52.21, $p < .001$) and Germany (B = 47.62, $p < .001$), indicating that school-level socioeconomic context substantially amplifies individual-level SES differences—consistent with network- and composition-based peer-effects research (Van Ewijk & Sleegers, 2010).

Associations with **disciplinary climate** were less uniform. Positive effects emerged in Finland (B = 37.49, $p = .041$) and Hungary (B = 24.73, $p = .031$), whereas estimates for Estonia and Germany were not statistically significant (see Figure 1). These patterns suggest that the role of behavioral climate varies across systems and may depend on country-specific instructional or organizational features.

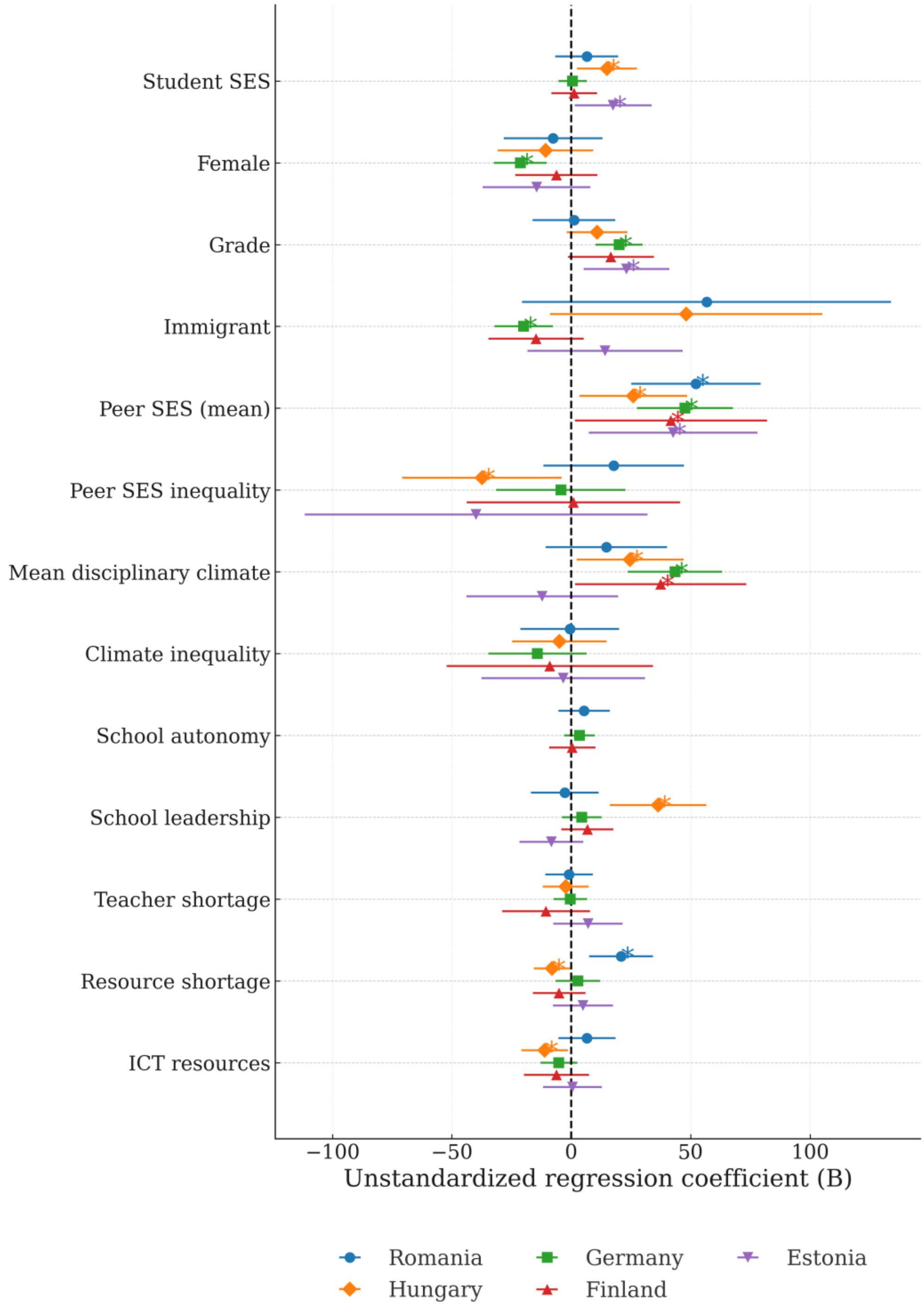

Figure 1. *Forest plot of multilevel coefficients for the five-country analysis. Proportion of migrant predictor was removed from the graph as it resulted in large SE.*

The **proportion of migrant-background students** was negatively associated with mathematics achievement in several models, although most coefficients were not statistically significant. An exception was Romania, where the estimate was large and negative (B = –599.44, *p* = .009). This pattern likely reflects the highly uneven distribution of migrant students across Romanian schools, resulting in pronounced between-school stratification rather than within-school compositional effects. The complete set of regression estimates for all countries is reported in Table 1.

Table 1. *Multilevel Regression Predicting Mathematics Achievement in Estonia, Finland, Germany, Hungary, and Romania.*

Country	Predictor	B	SE	t	p
Romania	Intercept	382.28	19.77	19.33	< .001
	Student SES (ESCS)	6.48	6.72	0.96	0.335
	Female (1 = yes)	-7.59	10.56	-0.72	0.472
	Grade (centered)	1.14	8.82	0.13	0.897
	Immigrant (1 = yes)	56.68	39.42	1.44	0.151
	Peer SES (mean ESCS)	52.19	13.82	3.78	< .001
	Peer SES inequality (var ESCS)	17.79	15.02	1.18	0.236
	Mean disciplinary climate	14.71	12.98	1.13	0.257
	Climate inequality (var)	-0.58	10.54	-0.06	0.956
	Proportion of migrants	-598.88	230.62	-2.6	0.009
	School autonomy (z)	5.38	5.5	0.98	0.328
	School leadership (z)	-2.73	7.24	-0.38	0.706
	Teacher shortage (z)	-0.92	5.08	-0.18	0.856
	Resource shortage (z)	20.84	6.82	3.05	0.002
	ICT resources (z)	6.6	6.09	1.08	0.279
Hungary	Intercept	459.12	15.56	29.51	< .001
	Student SES (ESCS)	14.93	6.41	2.33	0.020
	Female (1 = yes)	-10.78	10.22	-1.06	0.291
	Grade (centered)	10.82	6.5	1.66	0.096
	Immigrant (1 = yes)	48.12	29.1	1.65	0.098
	Peer SES (mean ESCS)	25.97	11.51	2.26	0.024
	Peer SES inequality (var ESCS)	-37.39	17.05	-2.19	0.028
	Mean disciplinary climate	24.66	11.45	2.15	0.031
	Climate inequality (var)	-4.97	10.11	-0.49	0.623
	Proportion of migrants	90.39	96.55	0.94	0.349
	School leadership (z)	36.38	10.32	3.52	< .001
	Teacher shortage (z)	-2.31	4.89	-0.47	0.637
	Resource shortage (z)	-8.0	3.9	-2.05	0.040
	ICT resources (z)	-11.1	4.98	-2.23	0.026
Germany	Intercept	502.75	15.5	32.44	< .001
	Student SES (ESCS)	0.53	3.04	0.17	0.862
	Female (1 = yes)	-21.33	5.62	-3.8	< .001
	Grade (centered)	20.02	5.04	3.97	< .001
	Immigrant (1 = yes)	-19.91	6.23	-3.2	0.001
	Peer SES (mean ESCS)	47.59	10.24	4.65	< .001
	Peer SES inequality (var ESCS)	-4.35	13.83	-0.31	0.753
	Mean disciplinary climate	43.42	10.07	4.31	< .001
	Climate inequality (var)	-14.15	10.5	-1.35	0.178
	Proportion of migrants	-7.83	25.08	-0.31	0.755
	School autonomy (z)	3.49	3.26	1.07	0.284
	School leadership (z)	4.36	4.23	1.03	0.303
	Teacher shortage (z)	-0.37	3.59	-0.1	0.918
	Resource shortage (z)	2.8	4.79	0.58	0.559
	ICT resources (z)	-5.19	3.93	-1.32	0.186
Finland	Intercept	382.68	31.63	12.1	< .001

Country	Predictor	B	SE	t	p
	Student SES (ESCS)	1.25	4.85	0.26	0.796
	Female (1 = yes)	-6.24	8.75	-0.71	0.476
	Grade (centered)	16.58	9.18	1.81	0.071
	Immigrant (1 = yes)	-14.74	10.17	-1.45	0.147
	Peer SES (mean ESCS)	41.78	20.52	2.04	0.042
	Peer SES inequality (var ESCS)	0.93	22.81	0.04	0.967
	Mean disciplinary climate	37.46	18.31	2.05	0.041
	Climate inequality (var)	-8.95	22.05	-0.41	0.685
	Proportion of migrants	69.35	42.68	1.62	0.104
	School autonomy (z)	0.4	4.94	0.08	0.935
	School leadership (z)	6.78	5.57	1.22	0.224
	Teacher shortage (z)	-10.56	9.4	-1.12	0.262
	Resource shortage (z)	-5.06	5.61	-0.9	0.368
	ICT resources (z)	-6.16	6.95	-0.89	0.376
Estonia	Intercept	491.34	24.31	20.21	< .001
	Student SES (ESCS)	17.55	8.24	2.13	0.033
	Female (1 = yes)	-14.52	11.49	-1.26	0.206
	Grade (centered)	23.15	9.13	2.53	0.011
	Immigrant (1 = yes)	14.17	16.58	0.85	0.393
	Peer SES (mean ESCS)	42.6	18.02	2.36	0.018
	Peer SES inequality (var ESCS)	-39.85	36.61	-1.09	0.276
	Mean disciplinary climate	-12.13	16.2	-0.75	0.454
	Climate inequality (var)	-3.38	17.49	-0.19	0.847
	Proportion of migrants	-4.85	75.5	-0.06	0.949
	School leadership (z)	-8.32	6.84	-1.22	0.224
	Teacher shortage (z)	7.01	7.42	0.95	0.345
	Resource shortage (z)	4.98	6.42	0.78	0.438
	ICT resources (z)	0.49	6.29	0.08	0.938

3.2 School-Level Structure (Model 2)

Including the school-level structural indicators—school autonomy, leadership, teacher shortages, resource shortages, and ICT resources—resulted in only modest gains in model fit across most education systems. This finding aligns with prior research suggesting that structural features account for relatively little additional variance once socioeconomic composition is taken into consideration (Akiba et al., 2007; OECD, 2023, 2024; Sirin, 2005).

Table 3. *Model fit indices for multilevel models of mathematics achievement in five countries. Model fit indices for multilevel models of mathematics achievement (PV1MATH) in five countries.*

Country	Model	*N* students	*N* schools	AIC	BIC	logLik
Estonia	Model 1: Student + peer + climate	195	195	2243	2282	−1110
Estonia	Model 2: + school structure	195	195	2246	2299	−1107
Finland	Model 1: Student + peer + climate	341	341	3908	3954	−1942
Finland	Model 2: + school structure	341	341	3911	3976	−1938
Germany	Model 1: Student + peer + climate	731	731	8213	8268	−4094
Germany	Model 2: + school structure	731	731	8218	8296	−4092
Hungary	Model 1: Student + peer + climate	205	205	2270	2310	−1123
Hungary	Model 2: + school structure	205	205	2254	2307	−1111
Romania	Model 1: Student + peer + climate	209	209	2364	2404	−1170
Romania	Model 2: + school structure	209	209	2359	2416	−1163

Note. Model 1 includes student-level SES, grade, gender, immigrant status, and peer SES and disciplinary climate. Model 2 additionally includes school autonomy, leadership, teacher shortage, resource shortage, and ICT resources.

The only meaningful improvement appeared in Romania (ΔBIC ≈ –12), driven primarily by resource shortages (B = 20.76, p = .002), which significantly predicted lower achievement (see Table 3).

3.3 Romanian Stratum Analyses

Given Romania's multilingual education system, additional analyses explored whether model patterns differed between Romanian-medium and Hungarian-medium strata.

Fixed-Effect Estimates by Stratum In the Romanian stratum (n = 5,933), student SES remained a significant positive predictor (B = 10.93, $p < .001$), and peer SES showed a large contextual effect (B = 77.51, $p < .001$). Girls scored significantly lower than boys (B = −20.38, $p < .001$), mirroring national Romanian PISA trends (see Figure 2.).

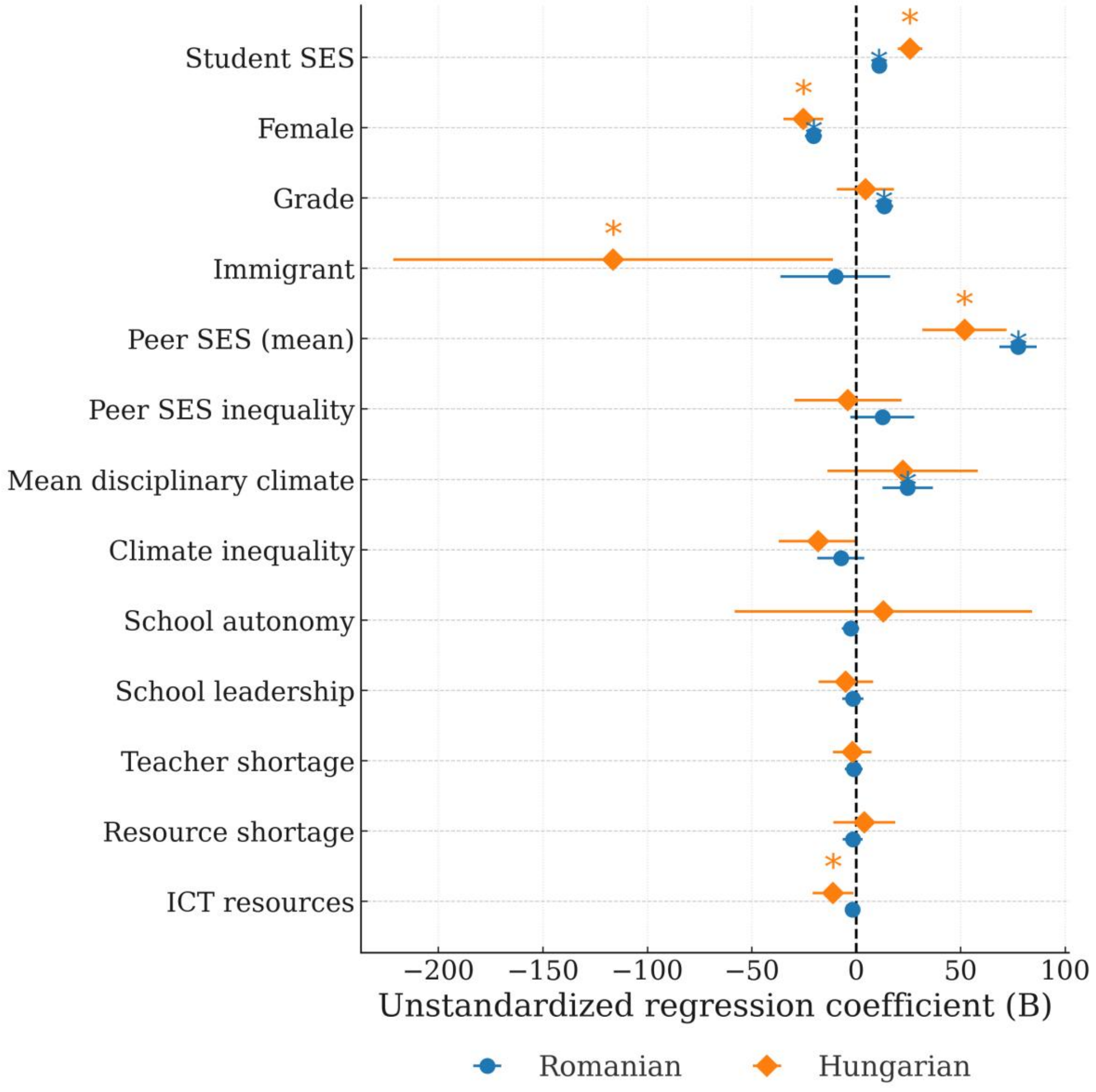

Figure 2. *Forest plot comparing coefficient patterns between Romanian and Hungarian strata. Proportion of migrant predictor was removed from the graph as it resulted in large SE.*

In the Hungarian stratum (n = 1,128), SES showed an even steeper gradient (B = 25.79, $p < .001$). Peer SES also remained a strong predictor (B = 51.90, $p < .001$). Structural variables were nonsignificant, likely due to the small number of schools (n = 34). The full regression tables are provided in Table 2.

Table 2. *Multilevel Regression Predicting Mathematics Achievement in Romanian and Hungarian Strata.*

Strata	Predictor	B	SE	t	p
Romanian subsample (N = 5,933)	Intercept	472.75	7.62	62.05	< .001
	Student SES (ESCS)	10.93	1.21	8.99	< .001
	Female (1 = yes)	-20.38	2.08	-9.81	< .001
	Grade (centered)	13.38	2.17	6.18	< .001
	Immigrant (1 = yes)	-9.98	13.39	-0.75	.457
	Peer SES (mean ESCS)	77.51	4.6	16.85	< .001
	Peer SES inequality (variance)	12.52	7.86	1.59	.113
	Mean disciplinary climate	24.61	6.16	4.0	< .001
	Climate inequality (variance)	-7.34	5.73	-1.28	.201
	Proportion of migrants (%)	-279.2	101.0	-2.76	.006
	School autonomy (z)	-2.68	2.12	-1.26	.208
	School leadership (z)	-1.57	2.61	-0.6	.547
	Teacher shortage (z)	-1.21	2.17	-0.56	.577
	Resource shortage (z)	-1.62	2.45	-0.66	.508
	ICT resources (z)	-1.75	1.9	-0.92	.356
Hungary subsample (N = 1,128)	Intercept	496.27	13.3	37.34	< .001
	Student SES (ESCS)	25.79	3.03	8.52	< .001
	Female (1 = yes)	-25.28	4.9	-5.16	< .001
	Grade (centered)	4.45	6.96	0.64	.523
	Immigrant (1 = yes)	-116.3	53.7	-2.16	.031
	Peer SES (mean ESCS)	51.9	10.3	5.02	< .001
	Peer SES inequality (variance)	-3.91	13.1	-0.3	.765
	Mean disciplinary climate	22.25	18.4	1.21	.225
	Climate inequality (variance)	-18.14	9.64	-1.88	.060
	Proportion of migrants (%)	104.0	248.0	0.42	.676
	School autonomy (z)	13.04	36.3	0.36	.720
	School leadership (z)	-4.93	6.68	-0.74	.460
	Teacher shortage (z)	-1.88	4.75	-0.4	.693
	Resource shortage (z)	3.86	7.55	0.51	.610

3.4 Model-Fit Comparisons

Model-fit indices for both models (student + peer + climate vs. full structural model) are shown in **Table 3** (five-country) and **Table 4** (Romanian strata).

Five-Country Fit Interpretation Across countries, Model 1 provided a strong baseline. Adding structural indicators (Model 2) did **not** meaningfully improve AIC or BIC values in Estonia, Finland, Germany, or Hungary. Only Romania showed modest improvement from adding structural predictors.

Romanian Strata Fit Interpretation In the Romanian stratum, Model 2 improved fit ($\Delta AIC = -7$; $\Delta BIC = -9$), indicating that structural factors—especially resource shortages—add explanatory value.

In contrast, in the Hungarian stratum, Model 1 remained preferable due to smaller BIC. Model-fit tables for both strata are presented in Table 4.

Table 4. *Model fit indices for multilevel models in Romanian and Hungarian strata. Model fit indices for multilevel models of mathematics achievement (PV1MATH) in Romanian student strata.*

Country/Stratum	Model	*N* students	*N* schools	AIC	BIC	logLik
Romania – Hungarian stratum	Model 1: Student + peer + climate	34	34	376	393	−177
Romania – Hungarian stratum	Model 2: + school structure	34	34	383	406	−177
Romania – Romanian stratum	Model 1: Student + peer + climate	174	174	1957	1995	−966
Romania – Romanian stratum	Model 2: + school structure	174	174	1950	2004	−958

Note. Strata refer to language-of-instruction demographic groups defined in the national sampling frame.

4. Discussion

The purpose of this study was to understand how far the socioeconomic gradients, peer-composition effects, disciplinary climate experience dynamics, and broader school-structural characteristics explain variations in mathematics achievement across countries in PISA 2022, and to comprehend how these processes work in Romania's linguistically stratified education system. Within a recent bibliography regarding school peer exposure and diffusion processes through networks (see Bramoullé et al., 2009; Sacerdote, 2011), we distinguished between the level and dispersion of peer SES and disciplinary climate. This distinction helped us think about whether normative influence is driven by the contextualized average or by the heterogeneity within schools. Given the well-documented evidence that minority-language schooling in Central and Eastern Europe does reflect cultural and organisational patterns that are distinctive (Kiss & Toró, 2025; Werfhorst & Mijs, 2010), Romania's linguistic strata provided a particularly interesting context to examine these effects.

At the level of the five countries examined, our findings were consistent with previous international evidence showing that individual socioeconomic status is one of the most robust predictors of standardised achievement in mathematics across countries in PISA (OECD, 2023, 2024; Sirin, 2005). More importantly, peer SES composition explained an effect that is as large as, and at times larger than, the individual SES effect, even after controlling student background variables, disciplinary climate, and structural school-level characteristics. This finding accords with peer-network theory, which holds that social exposure to peer characteristics are the primary channel through which externality occurs in formal learning settings (Sacerdote, 2011). Within a network framework, it should also be noted that SES variance, across schools, did not yield consistent associations across any of the school systems analyzed. Put in different terms, and similar to the situation of socioeconomic heterogeneity or other forms of gap, which seems to suggest differences at the level of the school hall but were not predictive of achievement, we can imply that socioeconomic heterogeneity within schools does matter in the considerations of mathematics achievement, once we account for the average normative and resources sleep into the mathematics context. In summary, with respect to mathematics learning, we see that exposure to advantageous peers means something, and much more than the distribution of socioeconomic advantage for students who are learning inside the same school.

The findings related to disciplinary climate also support the same line of thinking. In two of the school contexts examined, Finland and Hungary, where between-school variance is more pronounced variance in classroom climate, the mean climate showed a significant positive association. Whereas, the disciplinary-climate variance measure, taken in this study as a measure of within-school normative homogeneity (or heterogeneity) for behaviors, showed little predictive value. Again, this is consistent with peer-contagion views, which suggest that the dominant behavioral norm that is stabilized plays a bigger role than its variability in shaping within school networks (Kraft et al., 2016). Overall the SES and climate evidence bolsters an emerging theoretical perspective that composition type effects operate through normative processes largely rather than inequality per se.

As to school-structural measures of autonomy, leadership, teacher shortages, resource shortages, and ICT resource shortages, these showed more generally weak and inconsistent associations in the cross-national models. Romania appeared to be a notable exception; resource shortages at the school level had a more significant negative association for mathematics performance. The finding that addition of the structural indices did not substantially impact overall model fit is again consistent with earlier work that showed PISA's structural indices do little to explain variance at the internationally compressed study level if we account for the SES context (see Akiba et al., 2007; OECD, 2019; Sirin, 2005). The work here seems, in short, to lend itself to the developing argument, that peer-composition, SES, and normative factors matter far more in explaining variation than organizational, and governance dimensions within the PISA framework.

The analyses conducted at the Romanian stratum level provide an important layer of analysis to complement the cross-national findings. The Hungarian sector exhibited steeper socioeconomic gradients and stronger peer SES effects, in line with recent evidence for persistent socioeconomic and cultural differentiation between the Romanian- and Hungarian-language school sectors (Kiss & Toró, 2025). By contrast, the Romanian sector featured somewhat less steep SES associations, and a greater connection to disciplinary climate, which suggests some differences in normative functioning within separate linguistic contexts. Importantly, structural school-level indicators were not significant in either stratum, indicating that the differences between linguistic tracks are attributable more to compositional and normative considerations than to actual differences in formal resourcing or governance structures.

The analyses, across country and strata, addressed the study's central concerns pertaining to whether within-school SES inequality predicts achievement and whether disciplinary climate variance provides meaningfully more explanatory power than the average level of disciplinary climate. The evidence indicates clearly that neither SES variance nor climate variance is contributing meaningfully, once average level is included in the model. This pattern fits with a model of network-based diffusion in which contagion is located in the normative center of the peer group, rather than in its internal variation (Bramoullé et al., 2009); it also fits sociological accounts which propose that high-SES peer environments will yield collective benefits through higher overall expectations, stronger academic norms, and access to rich social networks (Coleman et al., 1966; Giletta et al., 2021; Li et al., 2020; Tsou, 2024).

This said, there are important limitations to consider. The cross-sectional nature of PISA does not provide the ability to draw causal inferences and a stronger test of peer diffusion would require longitudinal or quasi-experimental data. Although plausible values provide unbiased population estimates, they introduce additional sampling uncertainty, particularly in relatively small subsamples. The Hungarian stratum was sufficient for fitting random-intercept models, but may not have sufficient power to detect nuanced effects at the school-level.

Also, some of the structural indicators differ in concept meaning or reliability across national contexts, which limits strict cross-national comparability. Regardless of these limitations, this study makes an important contribution to ongoing debates on educational inequality across Europe. The analyses indicate that peer SES composition is a robust predictor across disparate education systems and has much more explanatory power than school structural indicators. The analyses also highlight that linguistic and ethnocultural sorting operate even within a single nation, with different socioeconomic gradients and normative dynamics. Policymakers should keep in mind the importance of reducing socioeconomic segregation, to strengthen disciplinary norms, and to consider the particular developmental and cultural needs of the minority-language school sector.

Overall, this study provides strong empirical evidence for a network-based conceptualization of peer effects and suggests that it is the average socioeconomic and normative backgrounds of peers, rather than inequality in those backgrounds, that matter for explaining mathematics achievement across European education systems.

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