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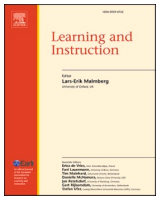

Competitive school environments and socioeconomic achievement inequality: A preregistered analysis of data from 69 countries

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ABSTRACT

Background: Competitiveness is a core feature of educational systems. We hypothesized that students from lower socioeconomic status (SES) backgrounds would feel less competent and perform worse in more competitive environments, as these environments conflict with their norms and values.
Aims: This preregistered study investigated whether school competitiveness widens SES achievement gaps in students' self-views and academic achievement.
Sample: The final analytical sample consisted of 315,095 fifteen-year-old students from 10,021 schools across 69 countries.
Methods: Program for International Student Assessment (PISA) 2018 data were analyzed using three-level hierarchical linear models that distinguished between perceived competitiveness (how competitive students perceive their school to be) and peer competitiveness (how competitive peers in school are). Outcomes included self-efficacy, self-perceived ability, mathematics achievement, and reading achievement.
Results: Contrary to our hypotheses, students from lower SES backgrounds had more positive self-views and performed better in more competitive environments, narrowing achievement gaps. While these interactions were statistically significant, effects sizes were small.
Conclusions: Competitive school environments do not necessarily widen SES achievement gaps. Our results suggest that students from socioeconomically disadvantaged backgrounds benefit more from competitive school environments than their more advantaged peers do. We discuss possible explanations (e.g., competitive environments may provide clear goals, structures, and rewards that foster engagement, which could be particularly beneficial for students who are less familiar with such environments).

1. Introduction

Competitiveness is deeply embedded in educational systems. Whether through standardized testing, ability-grouping, or public displays of outstanding achievements, students are often measured against their peers (Kohn, 1992). Competitiveness is often argued to increase achievement (Burguillo, 2010; Park, 2024). Yet, scholars contend that it may also reinforce educational inequalities by hindering the learning outcomes of students from lower socioeconomic status (SES) backgrounds. The cultural mismatch model suggests that students from lower SES backgrounds experience a mismatch between a competitive school environment and the values they have been socialized to hold (Goudeau et al., 2025). This mismatch could undermine students' self-views and achievement, thereby perpetuating socioeconomic disparities in educational outcomes. Such disparities are persistent and, in many countries, have widened over recent decades (Chmielewski, 2019).

Our preregistered study examines whether competitive school environments disadvantage students from lower SES backgrounds compared to their higher SES peers. We focus on secondary education, where achievement gaps tend to be pronounced (Reardon, 2018) and competition tends to be fierce (Eccles et al., 2013, pp. 74–85). This may be especially the case in countries with rigid educational tracking, where students are separated into distinct vocational, mixed, or academic tracks.

Specifically, we leveraged data from the 2018 Program for International Student Assessment (PISA) ($N = 315{,}095$) across 69 countries and over 10,000 schools. We examined how socioeconomic status (SES) moderates the relationship between competitive school environments and educational outcomes, focusing on and self-views (self-efficacy, self-perceived ability) and academic achievement (mathematics, reading).

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We employed three-level hierarchical linear regression models to distinguish *perceived competitiveness* (i.e., the degree to which students perceive their school environments as competitive) from *peer competitiveness* (i.e., the average level of students' competitiveness at school).

2. Theory & hypotheses

2.1. Competitiveness as a cultural norm in education

Educational systems can foster competition (Bartram, 2023; Brummelman & Sedikides, 2023; Mijs, 2021). In such systems, academic achievement is often regarded as a product of students' individual effort and ability, overlooking more structural causes of achievement inequality (Brown & Tannock, 2009). Competitive practices, such as ranking students or rewarding top performers, reinforce such merit-based thinking (Stephens et al., 2012). Teachers are more likely to adopt a normative rather than a criterion assessment method, emphasizing competition between students (Black & Wiliam, 1998). These competitive dynamics are reinforced through explicit practices, such as tracking, ability grouping, and grading on a curve, as well as through more subtle practices, such as displaying the best artwork, praising publicly, and defining success as a zero-sum game (Butera et al., 2024; Darnon et al., 2009; Jury et al., 2017; Kohn, 1992).

The question of whether competitiveness improves or hinders student outcomes has long been a focus of academic research. Some studies found that competitiveness predicts improved self-efficacy, self-perceived ability, and academic achievement (Baumann & Harvey, 2021; Chen & Liao, 2025; Park, 2024). Other studies found opposite effects (Baumann & Harvey, 2021; Posselt & Lipson, 2016; Senko & Dawson, 2017). And yet other studies have reported null effects (Elliot, 2020; Elliot et al., 2018; Murayama & Elliot, 2012). However, all these studies have focused on the average effects of competitiveness on achievement, rather than examining which students benefit or suffer from competitive school environments.

2.2. SES and the cultural mismatch with competitiveness

We rely on the Social Class–Academic Contexts Mismatch model (Goudeau et al., 2025) to understand how competitive educational environments can unevenly affect students from different socioeconomic backgrounds. This model highlights that schools often reflect middle- and upper-class norms, such as competitiveness, individualism, and self-promotion, which may clash with the values emphasized in lower SES families, such as modesty, solidarity, and fitting in.

In higher SES families, child-rearing practices often reflect the same meritocratic and competitive values found in educational contexts. Higher SES parents actively cultivate competitive behaviors from an early age to increase their children's chances for admission to selective educational institutions and attain occupational success in a competitive world (Friedman, 2013; Lareau, 2011). To reach this goal, higher SES parents are more likely to enroll their children in extracurricular activities, such as sports, music classes, and arts (Friedman, 2013). Moreover, parents often closely monitor their children's academic progress and actively guide their educational choices, such as encouraging them to attend summer camps and advanced classes (Galloway & Conner, 2015). By contrast, in lower SES families, child-rearing practices often reflect solidarity, fitting in, and working together, which are contrary to the culture of competition in education that rewards standing out (Kraus et al., 2012; Lareau, 2011; Piff et al., 2018). Parents from lower SES backgrounds often teach their children a "logic of constraint," which prioritizes others' needs and discourages behaviors like asking for help that can be interpreted as self-centered or inconsistent with their values (Calarco, 2014).

This mismatch—between the competitiveness of educational environments and the values endorsed by those from low-SES backgrounds—may undermine academic achievement in two stages (Goudeau et al., 2025). First, students from lower SES backgrounds experience a general sense of discomfort in the classroom. Second, in trying to explain this discomfort, they tend to attribute it to personal characteristics (e.g., ability, intelligence) rather than to contextual factors (e.g., Goudeau & Cimpian, 2021). This explanatory bias may lead students from lower SES backgrounds to blame themselves, triggering self-threat, which can lead them to form negative self-views (e.g., "I'm just not smart enough"). Consistent with this view, there is substantial evidence showing that children from lower SES backgrounds have more negative self-views: They feel less able, less able to cultivate their ability, and overall less worthy and deserving (for a review, see Brummelman & Sedikides, 2023). Important, these disparities in self-views are independent of children's actual abilities and achievement. That is, even when comparing children with the same level of ability and achievement, those from lower SES backgrounds have more negative self-views, which can then undermine academic achievement (Brummelman & Sedikides, 2023).

Although direct evidence is scarce, indirect evidence suggests that students from lower SES backgrounds may hold negative self-views and perform worse in more competitive contexts. For example, first-generation students (who tend to be from lower SES backgrounds) experience more imposter feelings and a lower sense of belonging in more competitive classrooms (Canning et al., 2020). Marginalized students also experience increased anxiety and depression in school environments they perceive to be competitive (Posselt & Lipson, 2016). More broadly, it is believed that individuals from lower SES backgrounds feel less equipped to cope with competitive environments and interpret these environments as a threat, leading them disengage (Sommet et al., 2024).

Specific characteristics of competitive environments, such as selection and assessment practices, can also widen SES-based gaps. In one experiment, first-generation students performed worse on math tasks after learning that universities are (vs. are not) competitive (Jury et al., 2015). In another experiment, lower SES students performed worse when achievement differences were rendered visible through hand-raising, likely because they perceived slower responses as evidence of inferior ability (Goudeau & Croizet, 2017; Goudeau & Cimpian, 2021). Such effects can be countered. Indeed, first-generation students earn higher grades (in fact, their grades were as high as those of their continuing generation peers) on assignments designed to benefit their learning (Smeding et al., 2013). First-generation students also perform better on tasks that foster collaboration rather than competition (Dittmann et al., 2020). Thus, existing evidence suggests that competitive school environments can undermine the self-views and achievement of lower-SES students, exacerbating existing disparities.

2.3. Present study

This study is the first to investigate, across many countries, whether students from lower SES backgrounds show more negative self-views and worse achievement in more competitive classrooms. We focused on two dimensions of school competitiveness: perceived and peer competitiveness. *Perceived competitiveness* refers to students' personal perceptions of how competitive their school environment is (Elliot et al., 2018). By contrast, *peer competitiveness* reflects the aggregated level of competitiveness of peers in a given school (Abril & Trinidad, 2022; King & Mendoza, 2020). Both theory (e.g., Brown et al., 1998; Murayama & Elliot, 2012) and research (e.g., Hemi et al., 2024; Ryan, 2001) suggests these forms of competitiveness may have distinct effects.

Using PISA 2018 data from over 300,000 students across more than 10,000 schools and 69 countries, we examined associations between both perceived and peer competitiveness and students' self-views and academic achievement through multilevel regression models. Our preregistered hypothesis was that students from lower SES backgrounds would be more adversely affected by (or benefit less from) competitiveness, such that the associations of students' perceived

competitiveness and peer competitiveness with students' self-views and academic achievement would be more strongly negative (or less strongly positive) for those with lower levels of SES.

Although not central to the manuscript, we also examined whether and why competitive classroom environments are more common in some countries than others. Educational tracking can foster competitiveness by creating classrooms that are more homogenous and therefore makes achievement differences more salient (Oakes, 2005). Specifically, we hypothesized a positive association between the degree of educational tracking and competitiveness, such that higher country-level tracking of educational systems would be positively related to students' perceived competitiveness and school-level trait competitiveness.

3. Data

We preregistered our hypothesis and analyses prior to accessing the data via the Open Science Framework: https://doi.org/10.17605/OSF.IO/F5Y23.

3.1. Participants

The Program for International Student Assessment (PISA) 2018 (OECD, 2019a) is a large-scale international survey assessing the knowledge and skills of 15-year-old students across 79 countries (N = 612,004). PISA assesses students' ability to apply their reading, mathematics, and science knowledge to real-world contexts. The computer-based survey uses a two-stage stratified sampling approach to ensure national representativeness. To allow for valid cross-country comparisons, results are scaled with Item Response Theory. PISA 2018 contains extensive contextual data on socioeconomic status, school environment and student attitudes. The dataset is publicly available on the OECD website, along with technical documentation and guidelines for analysis. Syntax used for data preparation and analyses is available on the OSF project page: https://osf.io/8um7t/overview.

We imposed three preregistered restrictions on the dataset. First, we excluded countries with complete missing data on one or more key variables (13%). Second, we deleted missing data listwise on the student level (25%). Several student-level background variables had higher levels of missing data, primarily due to PISA's rotated background questionnaire design. See online supplement S1 for a detailed overview of missing data. Third, we excluded schools with fewer than 20 participating students (~21%) (following a similar approach as Hofer et al., 2024). After listwise deletion, the final analytical sample consists of 315,095 students from 10,021 schools across 69 countries. All continuous variables in our models were standardized with a mean of 0 and a standard deviation of 1.

3.2. Measurement

Self-views. Self-views were operationalized through two indices. The index of self-perceived ability (SCREADCOMP) evaluates students' self-perception of their reading ability. It was constructed using an IRT-scaling model based on three items regarding reading fluency and comprehension (OECD, 2019b), such as "I am a good reader." The index of self-efficacy (RESILIENCE) measures a student's belief in their own ability (OECD, 2019b) It includes statements such as "I feel that I can handle many things at once." For both indices, students responded to items using a 4-point Likert scale ranging from "Strongly disagree" to "Strongly agree."

Mathematics and Reading achievement. Academic achievement was assessed using reading and mathematics scores. In PISA 2018, mathematical literacy was defined as the ability to apply mathematics in everyday contexts, requiring students to translate problems into mathematical structures and interpret the results in practical terms. Reading literacy was measured as the ability to understand, evaluate and integrate digital texts from multiple sources. Because students were not administered the full test battery, PISA employed PVs to estimate proficiency across the entire domain based on latent achievement scores. To account for measurement uncertainty, ten plausible values were used for each domain. Following Rubin's (2018) combination rules, estimates for each PV were combined to ensure reliable parameter estimates (Laukaityte & Wiberg, 2017). See online supplement S2 for a more detailed definition of mathematics and reading achievement and a description of the tests.

Perceived competitiveness. Perceived competitiveness was assessed using an index of perceived school competitiveness (PERCOMP) constructed by PISA. This was a combination of three questions: "Students seemed to value competitiveness," "It seemed that students were competing with each other," and "Students seemed to share the feeling that competing with each other was important" (OECD, 2019b).

Peer competitiveness. To measure peer competitiveness, we aggregated the students' individual trait competitiveness score (COMPETE) at the school level. The COMPETE index was constructed by PISA using students' responses to three statements about their attitudes towards competition (OECD, 2019b). To create a school-level measure of peer competitiveness, we computed weighted school means of COMPETE using a leave-one-out approach, whereby each student's own score was excluded when calculating the school mean for that student. In this way, each student's peer competitiveness score reflects the competitive dispositions of their peers rather than their own, avoiding the issue of students contributing to their own peer environment measure. Importantly, peer competitiveness was computed using the original PISA student weights rather than the senate weights, to ensure that the measure reflects the actual distribution of competitive dispositions within schools as they exist in the population. See online supplement S3 for more information on the construction of peer competitiveness.

Socioeconomic status. Students' socioeconomic status was measured using the Index of Economic, Social, and Cultural Status (ESCS) created by PISA. This composite index gives equal weight to three standardized components: parents' highest level of education (PARED), parents' highest occupational status (HISEI), and home possessions (HOMEPOS) (OECD, 2019b).

Control variables. In the exploratory analyses, we controlled for several demographic factors that have been found to be related to self-views, achievement, and competitiveness (e.g., Breda & Napp, 2019; Echazarra, 2020; Van Hek et al., 2019). Gender was included as a dichotomous variable (0 = male; 1 = female) to account for documented gender gaps in competitive preferences and academic self-concept. Immigration status was captured via the IMMIG index, which categorizes students into three distinct groups (i.e., native, first-generation, and second-generation) based on the birthplace of the student and their parents (OECD, 2019b). Finally, we accounted for the students' current grade level using the 'International Student Grade' variable. Given the potential for non-linear age effects on achievement and self-perceptions, grade was operationalized as a set of dummy variables with grade 10 serving as the reference category. Due to the low number of students in the 13th grade in our sample (N = 16), these observations were merged with grade 12.

We examined the internal consistently with Cronbach's alpha, computed separately within each of the 69 countries and pooled across all countries. Pooled within-country alphas were satisfactory for all scales: perceived competitiveness (α = .84), trait competitiveness (α = .77), self-efficacy (α = .78), and self-perceived ability (α = .76). For perceived competitiveness per-country alphas ranged from .73 to .92 (M = .83, SD = .04); for trait competitiveness .65 to .88 (M = .76, SD = .04); for self-efficacy from .65 to .90 (M = .78, SD = .04), for self-perceived ability .63 to .88 (M = .76, SD = .04). Full per-country reliability estimates are reported in online supplement S4.

4. Methods

We conducted our data analyses using three-level multilevel models,

with students nested within schools and schools nested within countries. We modelled country as a random level rather than fixed effects, as fixed effects would absorb all between-country variance and prevent estimation of country-level predictors such as school-tracking intensity. With 69 countries, random effects are also statistically appropriate, as multilevel models with this number of clusters produce reliable estimates even when clusters are not strictly randomly sampled (Elff et al., 2021).

To ensure equal country contribution regardless of population size, we applied senate weighting by rescaling PISA student weights equally across countries while preserving within-country differences in selection probability (Bol et al., 2014). PISA data were collected with a two-stage sampling design, schools were sampled first followed by students within each selected school. Sampling bias can thus arise both at the school and student level. To correct for this, each student is assigned a final weight (W_FSTUWT) that accounts for both the probability that the student' school was selected and the probability that the student was selected within that school. No separate school weights are included in the PISA student file, as the school-level probability is already incorporated into the final student weight. This is consistent with the approach recommended by PISA (OECD, 2009, see p. 219-221 for an example of a 3-level model). Combining student- and school-level weights in such models has been explicitly discouraged for large-scale assessment data (Rutkowski et al., 2010).

To obtain correct standard errors, we used the 80 replication weights provided by PISA via the Balanced Repeated Replication (BRR) approach, which corrects for the violation of simple random sampling assumptions due to PISA's clustered sampling design. We ran each model 81 times, once with the main student weights and once per replication weight, and standard errors were computed from the variability across estimates using PISA's recommended variance formula (OECD, 2009). We applied senate weighting to the replication weights for consistency in variance estimation. We conduced our analyses in R using the "lme4" package (Bates et al., 2015), with BRR variance estimation and plausible value handling implemented manually in line with PISA documentation (OECD, 2009).

We examined two outcome variables: self-views (self-efficacy and self-perceived ability) and achievement (mathematics and reading scores). We included three key predictor variables: SES, perceived competitiveness, and peer competitiveness. For each outcome variable, we estimated separate multilevel models, with SES included as a key predictor in all models, while analyzing the two dimensions of competitiveness independently. The interaction effects we tested followed a stepwise procedure. In the first step, we estimated a base model including SES and the relevant competitiveness variable (either perceived or peer competitiveness) as main effects. In the second step, we added the product term of the two variables to the model. This approach allows for a direct comparison of model fit between the model with and without the interaction term. To facilitate the interpretation of significant interactions, we computed simple slopes at conventional levels of the moderator variable (one standard deviation below the mean, at the mean, and one standard deviation above the mean). See online supplement S5 for the equations representing the regression analyses.

For the analyses with peer competitiveness, we deviated from the pre-registration by adding a random slope for SES on the school level where models converged. This addition was made in response to recent methodological advancements showing that, in cross-level interactions, omitting a random slope can overestimate fixed effects and underestimate standard errors (see Heisig & Schaeffer, 2019). Adding the random slope did not affect the results.

5. Results

5.1. Descriptive results

Table 1 presents pooled unstandardized descriptive statistics of the measures of self-views, performance and competitiveness. The sample was evenly distributed in terms of gender and consisted mainly of native students. Most students were in the 9th and 10th grade, 30.8 and 57.2 percent respectively. More detailed descriptive analyses, descriptive figures, and a full correlation matrix can be found in online supplement S6.

5.2. Multilevel results

5.2.1. Self-views

Table 2 shows standardized regression estimates for self-efficacy and self-perceived ability. SES was a moderately strong predictor of both self-view measures ($\beta \approx .110$ - $.185$, $p < .001$).

Students in schools with higher *peer competitiveness* did not report significantly higher self-perceived ability ($\beta = .006$, $p = .069$) nor significantly higher self-efficacy ($\beta = -.004$, $p = .922$). There were significant interactions between peer competitiveness and SES for self-efficacy ($\beta = -.007$, $p = .020$) but not for self-perceived ability ($\beta = -.005$, $p = .100$). Contrary to our hypothesis, students from lower SES backgrounds (more so than students from higher SES backgrounds) reported more positive self-efficacy in schools with higher peer competitiveness.

Students with higher *perceived competitiveness* had higher self-efficacy ($\beta = .192$, $p < .001$) and self-perceived ability ($\beta = .111$, $p < .001$). There was a significant interaction between perceived competitiveness and SES for self-efficacy ($\beta = -.016$, $p < .001$) and self-perceived ability ($\beta = -.010$, $p < .001$). Contrary to our hypothesis, students from lower SES backgrounds (more so than students from higher SES backgrounds) reported more positive self-views when they perceived their school as more competitive.

These results highlight differences between peer competitiveness and perceived competitiveness. While peer competitiveness showed

Table 1
Unstandardized descriptive statistics (N = 315,095).

	Mean	SD	N	%
Reading	476.08	100.21		
Mathematics	477.17	100.21		
Self-perceived reading ability	.05	.95		
Self-efficacy	.11	1.00		
Perceived competitiveness	.09	.99		
Peer competitiveness	.11	.31		
SES (ESCS-index)	−.19	1.07		
Gender				
Male			151,750	48.2
Female			163,345	51.8
Immigration background				
Native			281,621	89.40
Second-generation			18,805	5.97
First-generation			14,669	4.66
Grade				
7th			1057	.34
8th			8216	2.61
9th			96,926	30.80
10th			180,236	57.20
11th			27,623	8.77
12th			1038	.33

Note: Means and standard deviations for reading and mathematics are averaged across ten plausible values. All statistics are weighted using senate-adjusted student weights, giving each country equal contribution.

Table 2
Estimates of the multilevel models for self-views.

	Self-efficacy				Self-perceived ability			
	Model 1a	Model 1b	Model 2a	Model 2b	Model 3a	Model 3b	Model 4a	Model 4b
Intercept	.046***(.005)	.042***(.005)	.042***(.004)	.042***(.004)	−.063***(.005)	−.072***(.005)	−.066***(.005)	−.066***(.005)
Socioeconomic Status	.125***(.003)	.128***(.004)	.111***(.003)	.110***(.003)	.181***(.003)	.185***(.002)	.173***(.003)	.173***(.003)
Peer Competitiveness	.003(.026)	−.004(.041)			.010(.013)	.006(.015)		
SES * Peer		−.007*(.003)				−.005(.003)		
Perceived Competitiveness			.192***(.003)	.192***(.003)			.111***(.003)	.112***(.003)
SES * Perceived				−.016***(.003)				−.010***(.002)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Random effects								
School	.146	.143	.138	.138	.162	.152	.158	.158
Country	.237	.237	.230	.230	.230	.232	.227	.227
Residual	.963	.957	.946	.946	.937	.931	.932	.931
School SES Slope		.113				.124		
Fit Statistics								
AIC	1003697.807	1002752.62	992424.921	992336.052	987828.521	986529.873	983877.366	983843.182
BIC	1003847.056	1002933.851	992574.17	992495.961	987977.77	986711.104	984026.615	984003.092
LL	−501834.904	−501359.31	−496198.46	−496153.026	−493900.26	−493247.937	−491924.683	−491906.591
ICC Countries	.056	.056	.055	.055	.055	.057	.055	.055
ICC Schools	.021	.021	.020	.020	.027	.025	.026	.026
R^2 Marginal	.019	.019	.054	.054	.044	.045	.056	.056
R^2 Conditional	.094	.106	.124	.124	.123	.137	.133	.132
N Observations	315,095	315,095	315,095	315,095	315,095	315,095	315,095	315,095
N Schools	10,021	10,021	10,021	10,021	10,021	10,021	10,021	10,021
N Countries	69	69	69	69	69	69	69	69

Note. *p < .05, ***p < .001; controls include immigration status, gender, and grade.

minimal associations with students' self-views, perceived competitiveness was substantially and positively associated with both types of self-views. Yet, students from lower SES backgrounds (more so than their peers from higher SES backgrounds) fared slightly better with greater perceived and peer competitiveness, showing more positive self-views.

5.2.2. Academic achievement

Table 3 shows pooled standardized regression estimates for mathematics and reading scores. SES was a moderately strong predictor of both achievement measures ($\beta \approx .148$ - .167, $p < .001$).

Students in schools with higher *peer competitiveness* had lower mathematics ($\beta = -.049$, $p < .001$) and reading ($\beta = -.032$, $p < .001$) scores. There was a significant interaction between peer competitiveness

Table 3
Pooled estimates of the multilevel models for academic achievement.

	Mathematics				Reading			
	Model 1a	Model 1b	Model 2a	Model 2b	Model 3a	Model 3b	Model 4a	Model 4b
Intercept	.120***(.005)	.106***(.005)	.122***(.005)	.122***(.005)	−.008*(.004)	−.019***(.004)	−.007(.004)	−.007(.004)
Socioeconomic Status	.157***(.004)	.167***(.004)	.156***(.004)	.156***(.004)	.149***(.003)	.159***(.003)	.148***(.003)	.148***(.003)
Peer Competitiveness	−.049***(.007)	−.049***(.007)			−.032***(.006)	−.031***(.006)		
SES * Peer		−.011***(.002)				−.002(.002)		
Perceived Competitiveness			.022***(.002)	.022***(.002)			.012***(.002)	.013***(.002)
SES * Perceived				−.009***(.002)				−.009***(.002)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Random effects								
School	.399	.396	.390	.390	.400	.396	.395	.395
Country	.500	.499	.511	.511	.452	.447	.460	.459
Residual	.689	.682	.689	.689	.708	.702	.709	.709
School SES Slope		.124				.125		
Fit Statistics								
AIC	809504.4	807338.1	809317.2	809267.4	826728.6	824721	826676.9	826629.3
BIC	809653.6	807519.3	809466.5	809427.4	826877.8	824902.3	826826.1	826789.2
LL	−404738.2	−403652	−404644.6	−404618.7	−413353.0	−412343.5	−413324.4	−413299.7
ICC Countries	.283	.286	.294	.294	.236	.236	.243	.243
ICC Schools	.180	.180	.171	.171	.185	.184	.180	.180
R^2 Marginal	.081	.084	.082	.082	.080	.084	.082	.081
R^2 Conditional	.506	.519	.510	.509	.467	.478	.470	.470
N Observations	315,095	315,095	315,095	315,095	315,095	315,095	315,095	315,095
N Schools	10,021	10,021	10,021	10,021	10,021	10,021	10,021	10,021
N Countries	69	69	69	69	69	69	69	69

Note. *p < .05, ***p < .001; controls include immigration status, gender, and grade.

and SES in mathematics (β = −.011, $p < .001$), but not in reading (β = −.002, $p = .270$). Contrary to our hypothesis, students from lower SES backgrounds (more so than higher SES students) performed better in mathematics in schools with higher peer competitiveness.

Students with higher *perceived competitiveness* had slightly higher mathematics (β = .022, $p < .001$) and reading (β = .012, $p < .001$) scores. There was a significant interaction between perceived competitiveness and SES in both mathematics (β = −.009, $p < .001$) and reading (β = −.009, $p < .001$). Contrary to our hypothesis, lower SES students (more so than higher SES students) performed better when they perceived their school as more competitive.

The results highlight meaningful differences between peer and perceived competitiveness. Peer competitiveness was associated with poorer achievement (more so in mathematics than in reading), while perceived competitiveness was associated with slightly better achievement. Yet, lower SES students appeared to benefit more from both types of competitiveness, showing better achievement in mathematics and reading.

5.3. Visualization of interaction effects

In Figs. 1 and 2, we plotted simple slopes of the significant interaction effects to illustrate how the associations between competitiveness and the outcomes differ across SES groups. The figures plot predicted self-views (i.e., self-efficacy and self-perceived ability) and achievement (i.e., mathematics and reading) across the range of both dimensions of competitiveness for students at low (−1 *SD*), average (mean), and high (+1 *SD*) SES levels. The visual patterns show reductions in SES gaps as competitiveness increases. In competitive school environments, the self-views and achievement differences between lower and higher SES students narrow. Students from lower SES backgrounds tend to fare relatively better in more competitive school environments.

5.4. Robustness analyses

We conducted several sensitivity analyses to assess the robustness of our findings. Two analyses were pre-registered: (1) imputing missing data and (2) increasing the number of students per school from 20 to 30. See online supplement S1 for a description of how we imputed missing data with MICE.

In addition, we performed 3 non-preregistered sensitivity analyses (see online supplement 7 for the rationale and full results). Specifically, we (1) estimated models separately for boys and girls, (2) controlled for students' individual dispositions towards competitiveness, and (3) modelled peer competitiveness at the school level.

The effects of perceived competitiveness, including the negative interaction with SES, were robust across all specifications. The effects of peer competitiveness were more specification-dependent: the direct association with achievement was negative in the main analyses but became positive after accounting for individual trait competitiveness or when operationalized at the school level. The SES × peer competitiveness interaction was consistently negative in direction and was

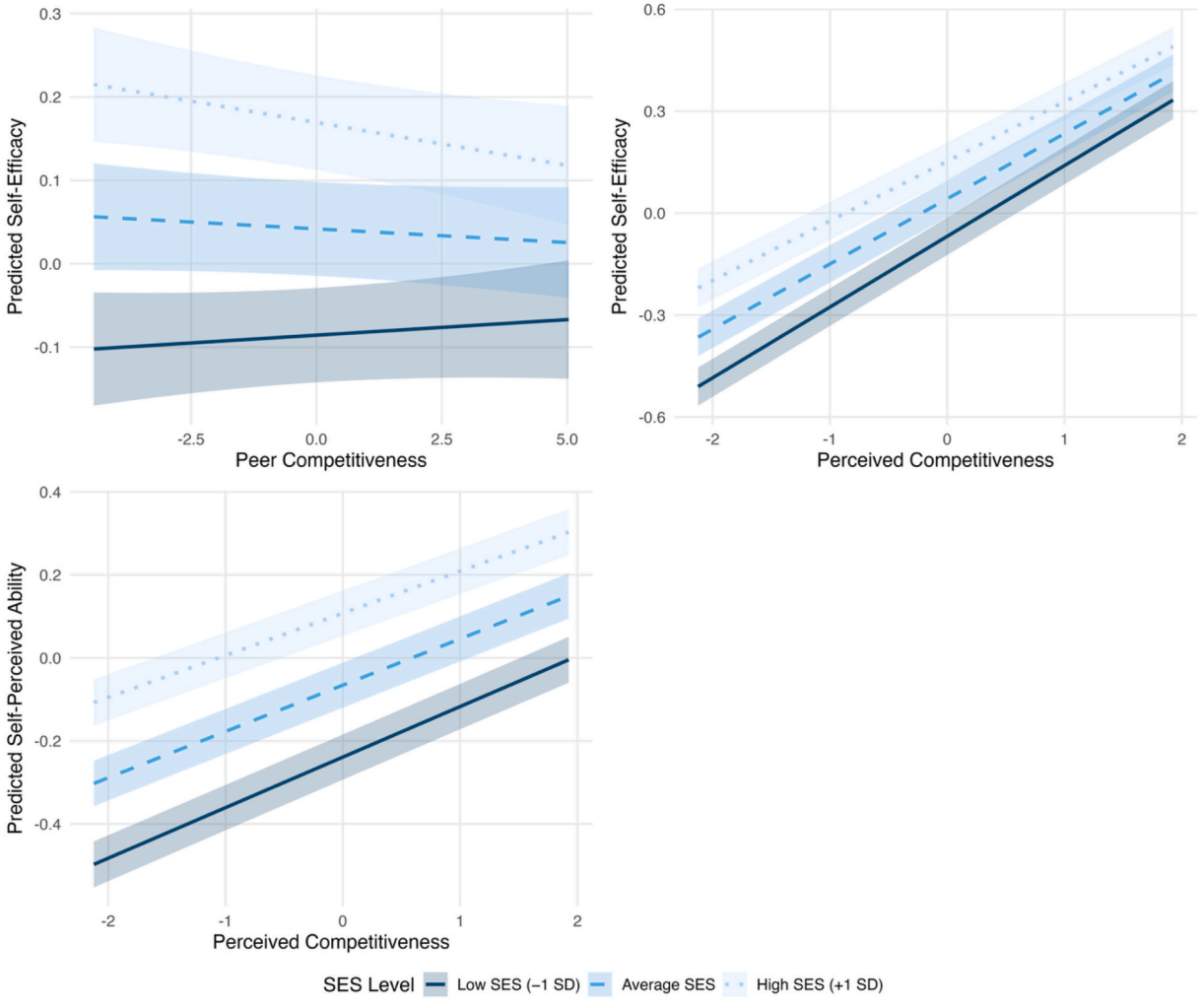

Fig. 1. Simple slopes for competitiveness for different levels of SES on self-views outcomes.

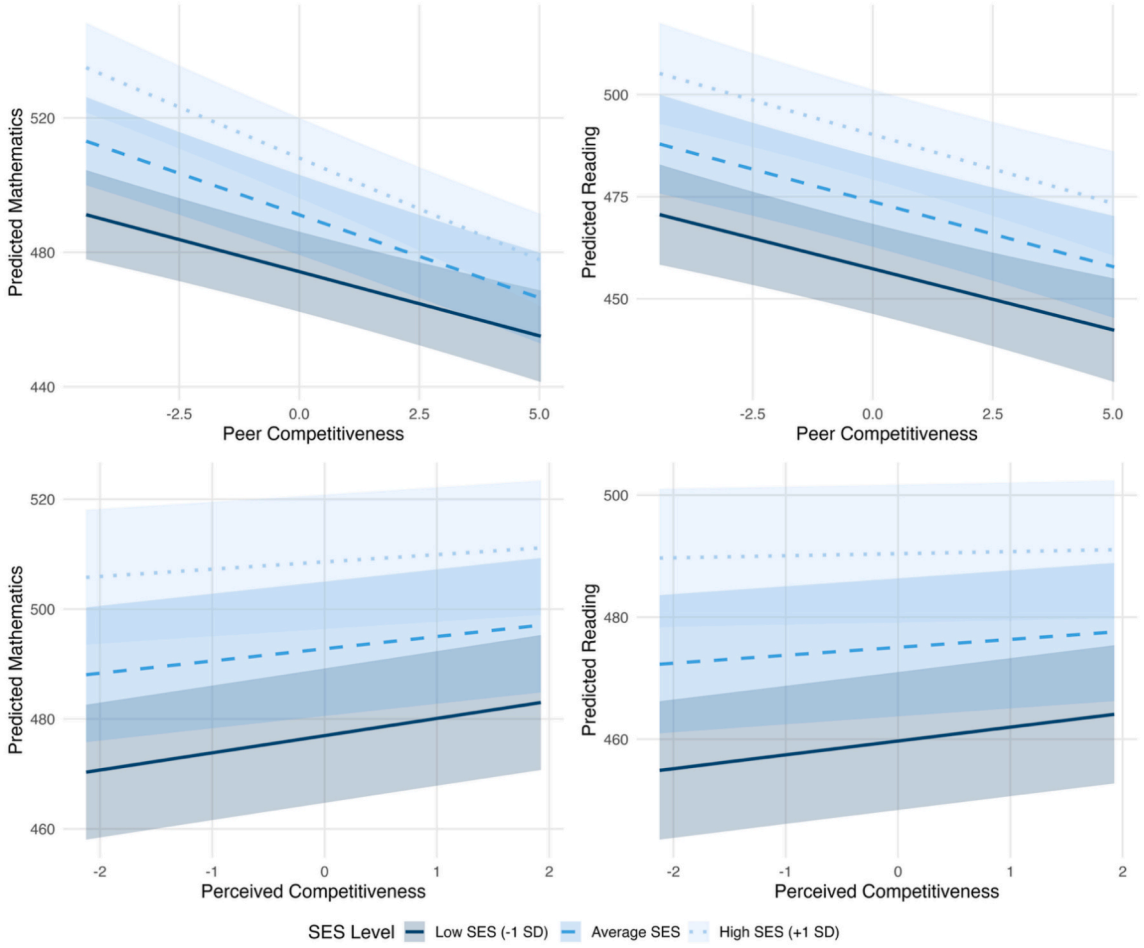

Fig. 2. Simple slopes for competitiveness for different levels of SES on achievement outcomes.

statistically significant for mathematics and self-efficacy in most specifications, though it did not reach significance in the imputed self-views models or when restricting to schools with at least 30 students. Detailed descriptions and results are available in online supplement S7.

Table 4
Standardized estimates of the multilevel models for the relationship between tracking and competitiveness.

	Peer competitiveness			Perceived competitiveness		
(Intercept)	−.038(.075)	−.038(.075)	−.039(.075)	−.021(.030)	−.027(.030)	−.027(.032)
Tracking indicators						
Age of selection	.050(.070)			.082**(.028)		
Number of programs		−.020(.074)			−.069*(.030)	
Composite scale			−.071(.148)			.043(.062)
Random effects						
Countries	.382	.385	.384	.061	.063	.068
Schools	.545	.545	.545	.033	.033	.033
Residual	.011	.011	.011	.885	.885	.885
Fit statistics						
AIC	369919.0	369918.5	369918.7	1069090.3	1069093.3	1069098
BIC	369865.2	369864.8	369864.9	1069144.1	1069147.1	1069151.8
LL	−184996.0	−184964.3	−184964.4	−534540.2	−534541.7	−534540,0
ICC Schools	.407	.409	.408	.062	.065	.069
ICC Countries	.581	.579	.580	.034	.034	.033
R^2 Marginal	.003	.000	.001	.007	.005	.001
R^2 Conditional	.988	.988	.988	.102	.102	.103
N Observations	346,411	346,411	346,411	346,411	346,411	346,411
N Schools	10,822	10,822	10,822	10,822	10,822	10,822
N Countries	69	69	69	69	69	69

*p < .05, **p < .01; listwise deletion.

5.5. Supplementary analyses

To explore contextual variation, we plotted the country-specific interaction coefficients between SES and the two dimensions of competitiveness for each student outcome (see online Supplement Figs. 7 and 8). Because higher SES is associated with more favorable self-views, a *negative* interaction coefficient indicates that higher levels of school competitiveness decrease the SES gap in the outcome, whereas a *positive* interaction coefficient indicates that the SES gap widens in more competitive school environments. Although country-specific interaction coefficients varied in direction (49% negative, 51% positive) and were mostly non-significant individually, the pooled cross-country estimates are negative and statistically significant, supporting the overall pattern we elaborate on in the discussion.

We further examined whether country-level educational systems, specifically between-school tracking, explain this variation. We ran three multilevel models for each competitiveness dimension (Table 4). Results showed no statistically significant association between tracking and peer competitiveness (age of selection: $\beta = .050$, $p = .477$; programs: $\beta = -.012$, $p = .266$; composite: $\beta = .071$, $p = .630$). However, we found small positive association between an earlier age of selection and perceived competitiveness ($\beta = .082$, $p = .003$), a small negative association for the number of programs ($\beta = -.070$, $p = .020$), and no significant relationship for the composite scale ($\beta = .043$, $p = .483$).

6. Discussion

Although SES-based disparities in education are well-documented (Chmielewski, 2019; Reardon, 2018), the role of competitiveness in shaping these gaps remains understudied. This pre-registered study addresses this caveat by testing whether competitive school environments are more detrimental, or less beneficial, to the academic achievement and self-views of students from lower SES backgrounds. Contrary to our hypotheses, students from lower SES backgrounds had more positive self-views and performed better in more competitive environments, narrowing achievement gaps. Effect sizes were small.

6.1. Theoretical implications

We theorized that competitiveness could widen SES gaps. Lower SES students are believed to experience a cultural mismatch between the values of their home environments, such as modesty and solidarity, and the competitive, individualistic norms in schools (Goudeau et al., 2025). They may feel less comfortable in competitive environments, engage less in self-promoting behaviors like asking for help (Calarco, 2014), and hold less positive self-views (Brummelman & Sedikides, 2023). By contrast, higher SES families actively encourage competitiveness through structured activities and academic monitoring. This emphasis on individualistic values can create a cultural mismatch for lower SES students, potentially putting them at a disadvantage (Goudeau et al., 2025). Contrary to our hypotheses, our findings did not reveal that lower SES students fared worse in more competitive school environments, regarding both perceived competitiveness and peer competitiveness. They showed more positive self-efficacy and self-perceived ability as well as somewhat better reading and mathematics achievement. Thus, our analyses showed that SES gaps were slightly but consistently smaller in more competitive school environments.

What explains our findings? One reason for the results might be that higher SES students, having grown up where academic competition is regularly reinforced, may see competitive environments as familiar and gain little additional motivational benefit, resulting in diminishing returns (Calarco, 2014; Lareau, 2011). Consistent with this, the benefit of competitiveness seems to weaken in more competitive schools where pressure is higher for everyone (Chen & Liao, 2025).

Another explanation suggests that competitiveness offers scaffolding to students from lower SES backgrounds. These students, while familiar with competition for material resources (Ellis et al., 2022), are often less exposed to academic competition. This novelty can activate scaffolding where clear goals, structure, and rewards foster engagement (Belland et al., 2013; Burguillo, 2010). These external cues can act as bridges that support students' motivation by making success feel achievable, especially for students exposed to less academic competitiveness. Our findings support this: Although students from lower SES backgrounds were less likely to perceive their schools as competitive, those who did showed greater gains and more positive self-views than higher SES peers. This scaffolding hypothesis aligns with research showing that extrinsic cues, such as competition, can enhance engagement in structured settings (Murayama & Elliot, 2012). For students from lower SES backgrounds, competitive environments provide an opportunity for scaffolding, increasing motivation in contexts where academic achievement may feel unattainable due to cultural mismatches or unfamiliarity with the system.

Prior research often focused on structural forms of competition, such as high stakes testing and selective admissions (Johnson & Johnson, 1989; Murayama & Elliot, 2012). These practices are tangible and likely to trigger cultural mismatches, potentially affecting lower SES students negatively (Goudeau & Croizet, 2017; Jury et al., 2015). Extending this work, our study examined students' perceived and peer competitiveness. Structural competitiveness may not always lead students to perceive their school as competitive or to their peers becoming more competitiveness. Thus, our work underlines the importance of examining students' subjective perceptions and their peers' dispositions.

While the overall trend indicate that SES gaps are narrower in more competitive school environments, there was substantial heterogeneity across countries. This heterogeneity suggests the effects of competition by SES varied across contexts; more research is needed to understand these cross-national differences.

7. Strengths, limitations, and future directions

We conducted a large-scale preregistered test of the effects of competitiveness, both peer and perceived, on students' achievement and self-views. Our study has some limitations. First, its cross-sectional design precludes causal inferences. Future research should leverage longitudinal data to study within-person changes in achievement. Second, peer competitiveness was measured at the school level, while it would ideally be assessed at the classroom level. Third, supplementary analyses suggest earlier educational tracking may link to higher perceived competitiveness. Future research should examine how structural features shape these dynamics.

Our findings have practical implications. Although effect sizes were small, our findings suggest that competitive school environment could play a role in reducing educational inequality. Students from lower SES backgrounds perceived lower levels of competitiveness yet benefited more from it in terms of self-views and achievement. This does not mean that schools should increase structural forms of competition, such as high stakes testing and selective admissions (Johnson & Johnson, 1989; Murayama & Elliot, 2012), because these have been linked to larger SES disparities (Goudeau & Croizet, 2017). Rather, schools can target students' subjective experiences of competition. Experiencing competition in itself may be motivating, raising academic expectations, fostering goal-oriented environments (Dobbie & Fryer, 2013), providing students an incentive to exert effort (Murayama & Elliot, 2012), especially when effort is rewarded consistently (Radl et al., 2026).

However, individual-level interventions alone are unlikely to be sufficient. In fact, in some cases, such individual-level interventions may run the risk of making children from lower SES backgrounds feel responsible for their predicament (Brummelman & Ziemer, 2023). A growing body of research therefore targets not individual students but adults in positions of authority, such as teachers (Hecht, Murphy, et al., 2023). For example, interventions can target teachers' bias against students from low-SES backgrounds (Rubie-Davies & Peterson, 2016)

and enable teachers to create *growth-mindset cultures* in their classrooms: conveying that all students can improve their ability, such as by setting high standards, supporting students in meeting these standards, and embracing mistakes as opportunities for learning (Hecht, Bryan, & Yeager, 2023). Future intervention research should examine when, how, and for whom creating healthy competition can benefit students from lower SES backgrounds.

8. Conclusion

Although students from lowers SES backgrounds on average underperform relative to their higher SES peers, our findings suggest that competitive school environments may help narrow these gaps rather than widen them. Unexpectedly, students from lower SES backgrounds appeared to benefit more from competitive school environments in terms of both self-views and academic achievement. Our findings suggest that competitiveness in education may not inherently exacerbate SES-based educational disparities.

CRediT authorship contribution statement

Nathalie Aerts: Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Conceptualization. **Thijs Bol:** Writing – review & editing, Supervision, Conceptualization. **Eddie Brummelman:** Writing – review & editing, Supervision, Conceptualization.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.learninstruc.2026.102414.

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