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Supporting Information for

Stunted Upward Mobility in a Learning Environment Reduces the Academic Benefits of Growth Mindsets

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SI Materials and Methods (Study 1)

1A. Materials. The data analyzed in this study came from the 2018 Programme for International Student Assessment (PISA), conducted by the Organization for Economic Co-operation and Development (OECD). The triennial assessment administers standardized tests on math, science, and reading literacy to 15-year-old students across 79 countries. In addition, student and school questionnaires are administered to obtain information about individual- and system-level factors that may be related to student outcomes. Hence, a comprehensive list of covariates could be included to permit the rigorous testing of our hypothesis. A country-level index of educational mobility was taken from the OECD's 2018 *Equity in Education* report (1).

To our knowledge, this is also the first instance of PISA that included a measure of growth mindsets of intelligence.

The PISA datasets are available to researchers through the main OECD website (https://www.oecd.org/pisa/data/).

1B. Study Population. The population included the 30 countries that had an index of educational mobility, after excluding Norway for missing data on growth mindsets of intelligence. From these countries, we included students and schools that had complete responses on our variables and covariates of interest.

Final sample. The sample sizes used in each model is presented in Table S1. Across all models, Spain was included in predicting math and science, but not reading scores as the data were not available. For the model without covariates, a total of 235,141 students were included. For models which included covariates, students from Austria, Belgium, Canada, and Denmark were excluded for missing data on specific student- or school-level covariates (see Section 1C). The remaining 160, 257 students represented, on average, 78.3% of the original sample in each country.

Table S1. Sample sizes included across the different models

	Model A (Without Covariates)		Model B, C, D, E (With Covariates)	
Country	$n_{schools}$	$n_{students}$	$n_{schools}$	$n_{students}$
Australia	728	12,079	546	8,913
Austria	282	6,464		
Belgium	161	4,526		
Canada	807	20,250		
Chile	252	6,747	180	4,728
Czech Republic	328	6,612	303	5,833
Denmark	343	6,570		
Estonia	230	5,143	228	4,991
Finland	206	5,318	175	4,414
France	252	5,846	189	4,296
Germany	210	4,235	159	2,943
Greece	241	6,138	203	4,975
Ireland	157	5,448	130	4,384

Israel	174	6,038	147	4,857
Italy	537	10,864	441	8,595
Japan	183	6,017	183	5,906
Korea	188	6,607	169	5,908
Lithuania	361	6,496	360	6,168
Netherlands	151	3,781	131	3,236
New Zealand	192	5,899	174	5,239
Poland	239	5,489	238	5,357
Russia	261	7,139	246	6,387
Singapore	166	6,601	164	6,443
Slovak Republic	356	5,566	317	4,693
Slovenia	309	5,996	271	5,163
Spain	1,088	33,748	846	24,995
Sweden	222	5,087	183	4,049
Turkey	186	6,811	184	6,640
United Kingdom	467	12,963	289	7,468
United States	163	4,663	130	3,676
Total (Math & Science)	9,440	235,141	6,586	160,257
Total (Reading – Excluding Spain)	8,352	201,393	5,740	135,262

Sample sizes of schools and students differed depending on whether the model included covariates. The inclusion of covariates meant excluding Austria, Belgium, Canada, and Denmark from the model, leaving a total of 26 countries from the full 30. For all model results on reading performance, Spain was excluded for missing data on reading literacy scores.

1C. Overview of Variables. The outcome variables of interest are math, science, and reading literacy performance (MSR) scores.

Plausible scores. The PISA assessment is based on a variant of matrix sampling where each student was only administered a subset of test questions from the total item pool. More specifically, different students answered different yet overlapping sets of items. The nature of this methodology requires the use of item response theory models to infer each student's ability level and allow performance comparisons between students. Instead of directly estimating a student's ability or intelligence level, a probability distribution for a student's ability is estimated. Plausible values are random draws from this estimated distribution for a student's level of ability (2). In PISA 2018, and in each subject, each student is drawn a set of 10 PVs that provides a "plausible" representation of their level of ability. The exact procedure for using these PVs is described in Section 1D.

Growth mindsets of intelligence. The PISA 2018 student questionnaire included a one-item measure of growth mindsets of intelligence, "Your intelligence is something about you that you can't change very much", adapted from Dweck's original scale (3). Students responded on a four-point Likert scale from strongly disagree to strongly agree. The item scores were reversed such that a higher score indicated greater endorsement of a growth mindsets.

Educational mobility. We obtained the country-level index of educational mobility from the OECD's 2018 "Equity in Education" report (https://www.oecd.org/publications/equity-in-education-9789264073234-en.htm; p. 186, Table 2.22). It measures the percentage of individuals from low-education households who eventually graduated from tertiary education. Low-education households were defined as having parents who did not complete upper secondary education. Countries deemed to be higher on educational mobility were the ones where a greater proportion of individuals from low-education households completed tertiary education. The values for England and Northern Ireland were aggregated to form a composite value for the United Kingdom.

Student-level covariates. The PISA student questionnaire included several self-report measures of motivation and goal pursuit, alongside the demographic variables of age, gender, and socioeconomic status. Unless mentioned otherwise, positive values on the following variables indicate greater endorsement of the construct compared to the average student across OECD countries.

i) Grit: Referred to in PISA as the motivation to master tasks, students indicated their extent of agreement to four items, "I find satisfaction in working as hard as I can", "Once I start a task, I persist until it is finished", "Part of the enjoyment I get from doing things is when I improve on my past performance", and "If I am not good at something, I would rather keep struggling to master it than move on to something I may be good at". The items were on a four-point Likert scale, ranging from strongly disagree to strongly agree ($\alpha = 0.76$). Belgium had missing data on this variable.

ii) Self-efficacy: Students answered the following five items, "I usually manage one way or another," "I feel proud that I have accomplished things," "I feel that I can handle many things at a time," "My belief in myself gets me through hard times," and "When I'm in a difficult situation, I can usually find my way out of it." Items were on a four-point Likert scale, ranging from strongly disagree to strongly agree ($\alpha = 0.77$).

iii) Socioeconomic status (SES): PISA refers to this index as the economic, social, and cultural status (ESCS). It is computed from three variables relevant to family background: (a) parents' highest educational qualification, (b) parents' highest occupational status, and (c) home possessions. The first two correspond to the highest qualification or status of either parent. Occupational status was coded and mapped to the international socio-economic index of occupational status (ISEI), to which higher ISEI scores indicate higher levels of occupational status. For home possessions, students reported the availability of 16 household items (of which three were country-specific indicators of wealth) and the amount of possessions and books they had at home. ESCS was computed by giving equal weight to each of the three components, which were standardized across all countries and economies. If more than one of the three variables had missing data, ESCS was not computed for that student.

School-level covariates. The PISA school questionnaire was completed by the principal of each school and provided background information about the quality of the learning environment and the availability of educational resources.

i) Shortage of educational material and staff: Eight items were used to measure each principal's perception of potential factors hindering the quality of teaching in school, "Is your school's capacity to provide instruction hindered by any of the following issues?" Four items inquired about the shortage of educational material (e.g., textbooks, IT equipment, library or laboratory material) and the deficits in physical infrastructure (e.g., building, grounds, heating/cooling, lighting and acoustic systems), "a lack of educational material/physical infrastructure" and "inadequate or poor quality educational material/physical infrastructure." Items were on a four-point Likert scale, ranging from "not at all" to "a lot". Higher scores indicated that principals viewed the amount or quality of resources in their schools to be a hindrance to teaching quality ($\alpha = 0.84$).

ii) Learning-hindering behaviors: This 11-item index measured the perceived extent to which learning in schools were hindered by certain maladaptive behaviors exhibited by students or teachers. Items included "Students skipping classes," "Students use of alcohol or illegal drugs", "Teachers not meeting individual students' needs," and "Teachers not being well prepared for classes." Similarly, a four-point Likert scale, ranging from "not at all" to "a lot" was used. Higher scores were indicative that such behaviors hindered learning to a greater extent ($\alpha = 0.86$).

iii) Student-teacher ratio: This was obtained by dividing the number of enrolled students by the number of teachers in each school. Schools with higher student-teacher ratios indicated that each teacher was taking on larger classes. Austria and Canada had missing data on this variable.

iv) Proportion of fully certified teachers: The number of fully certified teachers in a school was divided by the total number of teachers. Denmark had missing data on this variable.

Country-level covariates. As the PISA dataset did not provide any country-level variables, we drew these indices from several external sources.

i) Gini index: Country estimates for income inequality based on disposable income were drawn from the Standardized World Income Inequality Database (SWIID; https://fsolt.org/swiid/). The index has been widely utilized (4–6) due to its high degree of comparability and extensive coverage across 196 countries (7). The database compiles Gini indices from a vast number of sources, such as the OECD Income Distribution Database, the World Bank's PovcalNet, the UN Economic Commission for Latin America and the Caribbean, and other national statistical offices around the world. The Luxembourg Income Study data serves as the standard of comparability for the SWIID. We used the latest available data for each country, majority of which were from 2017. Exceptions were Australia (2016), Japan (2015), Russia (2016), Slovak Republic (2016), Turkey (2018), and United Kingdom (2018). Gini values range from 0-100%, with higher scores on this index indicating a greater degree of income inequality in a country.

ii) Social mobility index (SMI): Provided by the World Economic Forum in their report (WEF; 2020), the index considers the five key dimensions of health, education, technology access, fair work opportunities, and social protection and inclusive institutions (8). These dimensions are construed at the country-level as a means towards achieving greater socioeconomic mobility. Indices for the dimension of education include percentage of pre-primary enrolment, percentage of children below minimum proficiency, and the percentage of youths not in employment, education, or training (NEET), none of which directly pertains to the upward mobility of the disadvantaged.

iii) Gross domestic product (GDP) per capita: National estimates from the World Bank (https://data.worldbank.org/indicator/NY.GDP.PCAP.CD; accessed 9th February 2020) were used. All countries in the final analysis used the latest data from 2018.

iv) Educational expenditure: An objective indicator of educational spending by the government per secondary school student as a percentage of GDP per capita. The index was sourced from the UNESCO Institute of Statistics (UIS; http://data.uis.unesco.org; accessed 14th February 2020) and provided 2016 data for most countries. Exceptions include Italy (2015) and Singapore (2017). As there was no data provided for Russia, we imputed a value using information from a conceptually similar variable, the total government expenditure on education as a percentage of GDP. Based on data from 2016 and across a sample of 80 countries, the two variables were highly correlated (r = .51).

1D. Analyses. Multi-level mixed-effects models were conducted using a maximum likelihood estimator with robust standard errors and optimized using the expectation maximization algorithm on Mplus Version 8.3 (9). Dataset and syntax for the main analyses can be found at https://osf.io/zyv89/?view_only=f2e58c3713b245baaaac09aac5a6df50

Centering of predictors. All predictor variables were grand-mean centered at their respective levels of measurement to facilitate the interpretation of the intercepts, except for growth mindsets, which was group-mean centered by subtracting the mindsets aggregate for each school. This method of centering removes the variance between schools and countries, leaving only variance that captures student-level differences in mindsets (10). Similarly, school-level differences in mindsets were obtained by subtracting the aggregate for each country. This created three growth mindsets variables, one at each level of measurement, that were all entered into the final model.

The centering of variables around the group-mean is a common practice in multilevel models (11). When the data is hierarchical in nature, any estimated effects using raw, uncentered variables will generally comprise a confounding of both individual- and cluster-level effects. In the case of the present study, the effect of the uncentered mindset variable on performance would conceptually have been a composite of 1) the student-level trait mindset, 2) the school-level mindset average (aggregated across students), and 3) the country-level mindset average (aggregated across schools) that predicts performance. The effect becomes an "inappropriate estimator of the person-level effect" and is an "uninterpretable blend" of effects (10, p. 139).

Hence, group-mean centering permits us to tease out these student-level effects from the higher-level contextual effects, and creates a more precise and meaningful measure of student-level mindsets (12, p. 563). This is particularly important as we hypothesized that country-level educational mobility moderates the effect of growth mindsets on achievement at the student level.

Sampling weights. Even though students were randomly sampled in PISA, the selection probabilities of the students vary (2, 13). For example, certain sectors of the school population may be intentionally under-sampled because the schools are either very small or located in geographically remote areas. In other cases, schools may be over-sampled due to a national interest in analyzing specific sub-populations. The weights also serve to correct for student and school non-response. Randomly sampled students or schools may have refused to participate, causing certain sub-populations to be under-represented in the data unless weighting adjustments were made. In all our analyses, the sampling weights provided by PISA were included at the student level to correct for these biases.

Handling plausible values. Through Mplus, plausible values for student performance were handled as recommended using a multiple imputation approach, by estimating the regression coefficients and their corresponding standard errors on each of the ten plausible values provided for each subject, before combining the results together (14, 15).

Multilevel models. As reported in the main text, the intraclass correlations (ICCs) revealed that a substantial degree of variation in MSR scores could be explained by the school and country effects. To account for the dependence, we modelled a hierarchical linear model with students nested in schools, which were nested in countries. Intercepts, representing mean student performance, as well as the student-level growth mindsets to performance coefficient, were allowed to vary across school and countries. These constituted the random effects in our final model, which are represented by the equations shown below.

Student-level:

$$SCORE_{ijk} = b_{0jk} + b_{1jk}\left(GMindsetL1_{ijk}\right) + X_{ijk}\delta + r_{ijk}$$

School-level:

$$b_{0jk} = \eta_{0k} + S_{jk}\delta + \zeta_{0jk}$$
$$b_{1jk} = \eta_{1k} + \zeta_{1jk}$$

Country-level:

$$\eta_{0k} = \gamma_{00} + C_k\delta + u_{0k}$$
$$\eta_{1k} = \gamma_{10} + \gamma_{11}(EduMobility_k) + u_{1k}$$

At the student-level, $SCORE_{ijk}$ represents the PISA performance of student i from school j in country k on math, science, or reading literacy. b_{0jk} is the mean student score and b_{1jk} is the coefficient for the growth mindsets to performance relationship, both allowed to vary across schools. $GMindsetL1_{ijk}$ is the student's group-mean centered growth mindsets score. Student-level covariates are represented by the vector term $X_{ijk}\delta$ where δ is the vector of regression coefficients that accompany a vector of covariate scores, X_{ijk}. Prediction residuals are represented by the random error component, r_{ijk}.

At the school-level, the student-level intercept b_{0jk}, is modelled to be predicted by the mean school performance η_{0k}, and a host of school-level covariates are represented by a vector term $S_{jk}\delta$ comprising the covariate scores and their coefficients. ζ_{0jk} is specified as the error component that permits random student-level intercepts across schools. Similarly, b_{1jk} is predicted by fixed effect η_{1k}, which is the average growth mindsets coefficient across schools, and ζ_{0jk}, which specifies the random slopes across schools.

At the country-level, η_{0k} is predicted by γ_{00}, which is the mean performance across all countries, alongside the covariate vector term $C_k\delta$ and error term u_{0k}. The growth mindsets coefficient at the school-level η_{1k}, is predicted by the average coefficient across countries γ_{10}, and the random error term u_{1k}. Most importantly, γ_{11} characterizes the cross-level interaction in our model, by representing the coefficient of educational mobility that predicts the growth mindsets to performance relationship at the student-level. $EduMobility_k$ is the country score on educational mobility.

Sample size differences in covariates-exclusive model. For the test without covariates (Model A), supplemental analyses were run to examine the extent to which the results changed depending on whether a sample size of 26 or 30 countries were used. As shown in Tables S2 and S3, the results were largely similar across the two samples. The unstandardized regression coefficient for the cross-level interaction, mindsets × educational mobility, was marginally higher by 12.1% across MSR scores when all 30 countries were included. In addition, the direction and pattern of effects were identical across both sample sizes. Given the high similarities in results, we chose to present the more comprehensive sample of 30 countries.

Robustness checks with double-moderation. Additional tests for the robustness of the cross-level interaction effect were conducted using double moderation models, by including SMI and GINI separately as additional moderators alongside educational mobility. As reported in the main text, The mindsets × educational mobility interaction remained virtually unchanged in the new models. Further, neither Gini nor SMI emerged as a significant moderator on any subject. The full model coefficients and parameter estimates are reported in Tables S4 and S5.

Supplemental analysis with SES. Further analyses examined whether the moderating role of educational mobility applied to students from both high- and low-SES backgrounds (Table S6). SES was group-mean centered at the student and school level while grand-mean centering was applied to SES at the country level. Consistent with the main models, the two-way interaction between educational mobility and growth mindsets was mostly significant and highly similar across both high and low levels of SES (Table S7). This is consistent with the overall non-significant three-way interaction between educational mobility, growth mindsets, and SES (b = -0.07, SE = 0.04, P = 0.107 for math; b = -0.05, SE = 0.03, P = 0.064 for science; and b = -0.02, SE = 0.03, P = 0.605 for reading). Hence, the benefits of growth mindsets were evident for both advantaged and disadvantaged students, especially in high-mobility countries and 2) reduced educational mobility is associated with reduced benefits for both groups of learners. Extending from Figure 2 shown in the main text, Figure S1 further breaks down SES into deciles.

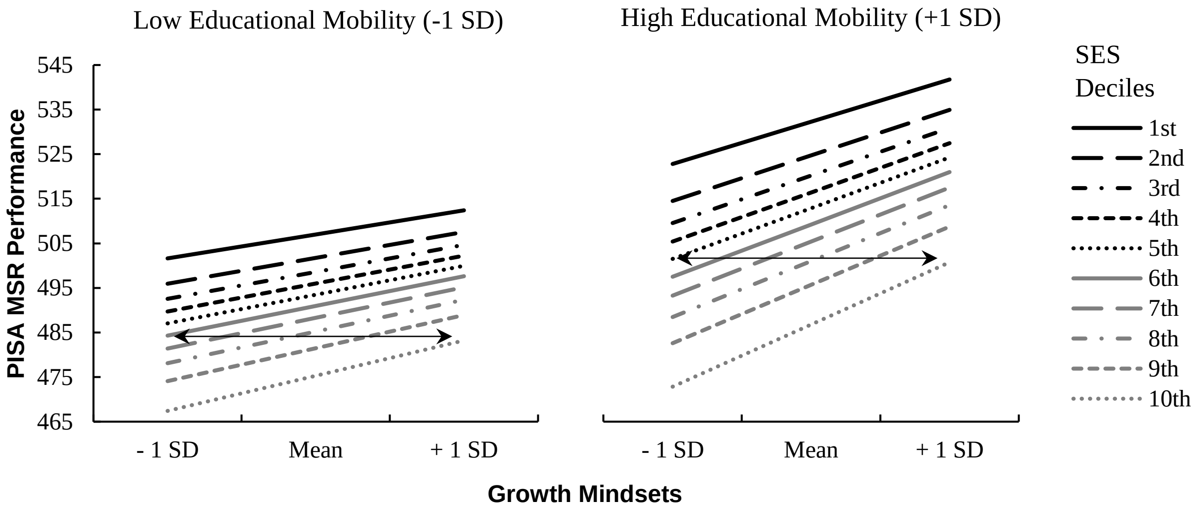


Figure S1. Graphical pattern depicting the relationship between growth mindsets, educational mobility, and SES (as deciles) in predicting PISA performance across math, science, and reading literacy scores (Study 1). The left and right panels respectively correspond to environments of low and high educational mobility. Black lines represent the top half of the SES spectrum, while gray lines represent the lower half. Two-sided arrows on each panel show the extent to which students from the lowest SES deciles with strong growth mindsets are able to perform as well as students from the upper SES deciles with weak growth mindsets.

We conducted descriptive analysis to examine the potential for growth mindsets to reduce the performance gap between students from low- and high-SES backgrounds (16). Specifically, we examined the performance of students with strong growth mindsets (+1 SD) from families in the bottom SES decile and compare it with that of students with weak mindsets (-1 SD) from families in top SES deciles (Fig. S1). In a high-mobility country (+1 SD), students with strong mindsets from families in the bottom decile can perform nearly as well as students with weak mindsets from families in the 5^{th} decile. In a low-mobility country (-1 SD), however, students with strong mindsets from families in the bottom decile can only perform as well as students with weak mindsets from families in the 6^{th} decile. In other words, as the beneficial impact of growth mindsets weakens from high- to low-mobility countries, the potency for growth mindsets to narrow the performance gap is also reduced.

While the main objectives of these analyses were to examine whether the moderating role of educational mobility applied to students from both high- and low-SES backgrounds, two findings that are not theoretically important to the current investigation are worth mentioning (Table S6). First, growth mindsets interacted with SES to predict academic achievement, especially for science (b = -1.66, SE = 0.30, P < 0.001) and reading (b = -1.74, SE = 0.45, P < 0.001) scores. The effects of growth mindsets were stronger among low-SES, as opposed to high-SES, students. This pattern is broadly consistent with past research that growth mindsets tend to be more impactful for disadvantaged or at-risk students (17–19). Second, SES interacted with educational mobility to predict academic achievement, especially for science (b = 0.29, SE = 0.14, P = 0.039) and reading (b = 0.29, SE = 0.12, P = 0.017) scores. The positive effect of SES on student achievement is larger in countries with higher educational mobility. Hence, educational mobility predicts improved learning of not only disadvantaged but also advantaged students; in fact, it predicts greater improvement in the learning of advantaged students (Figure 1). This intriguing pattern deserves further investigation.

Table S2. Supplemental results: Comparison of Model A cross-level interaction effects (student-level growth mindsets × educational mobility) across different sample sizes

Variable	Math			Science			Reading		
	b	SE b	***β***	*b*	SE b	***β***	*b*	SE b	***β***
Model A: *k* = 30									
Student-level variables									
GM L1	10.21***	1.03	0.09	12.57***	1.18	0.12	14.13***	1.30	0.12
School-level variables									
GM L2	65.90***	7.37	0.20	71.48***	6.95	0.21	84.59***	6.51	0.25
Country-level variables									
GM L3	-24.35	27.49	-0.05	-5.66	24.90	-0.01	9.96	24.19	0.02
Educational mobility	0.83	0.46	0.10	0.90	0.46	0.10	0.96*	0.45	0.10
Cross-level interaction									
GM L1 × educational mobility	0.32***	0.10	0.03	0.40***	0.12	0.04	0.39***	0.12	0.04
Intercept	495.94	4.47		495.85	3.97		494.65	3.69	
Model A: *k* = 26									
Student-level variables									
GM L1	10.13***	1.15	0.09	12.53***	1.30	0.12	14.08***	1.44	0.12
School-level variables									
GM L2	64.67***	8.00	0.20	68.70***	7.87	0.21	83.00***	7.39	0.25
Country-level variables									
GM L3	-26.86	30.99	-0.05	0.35	27.95	0.00	16.55	27.59	0.03
Educational mobility	0.90	0.52	0.11	0.91	0.53	0.10	0.93	0.51	0.10
Cross-level interaction									
GM L1 × educational mobility	0.28*	0.11	0.03	0.36**	0.13	0.04	0.34**	0.13	0.03
Intercept	496.64	5.00		497.92	4.46		497.03	4.25	

Values are unstandardized (*b*) and standardized coefficients with standard errors. GM, growth mindsets - L1,2,3 differentiates student, school, and country level of measurement. *k* = number of countries. *P* values: $*P < 0.05$, $**P < 0.01$, $***P \leq 0.001$.

Table S3. Supplemental results: Comparison of Model A simple slope effects (student-level growth mindsets × educational mobility) across different sample sizes

Simple slopes of GM L1 predicting performance	Math			Science			Reading		
	b	SE b	***β***	*b*	SE b	***β***	*b*	SE b	***β***
Model A: *k* = 30									
Low EM (-1 SD)	6.77***	1.25	0.06	8.36***	1.35	0.08	9.94***	1.45	0.08
Mean EM	10.21***	1.03	0.09	12.57***	1.18	0.12	14.13***	1.30	0.12
High EM (+1 SD)	13.64***	1.63	0.13	16.78***	2.02	0.15	18.33***	2.09	0.16
Model A: *k* = 26									
Low EM (-1 SD)	7.20***	1.39	0.07	8.76***	1.50	0.08	10.40***	1.59	0.09
Mean EM	10.14***	1.15	0.09	12.53***	1.30	0.12	14.08***	1.44	0.12
High EM (+1 SD)	13.08***	1.84	0.12	16.29***	2.23	0.15	17.75***	2.36	0.15

Values are unstandardized (*b*) and standardized coefficients with standard errors. EM, educational mobility. *k* = number of countries. *P* values: $*P < 0.05$, $**P < 0.01$, $***P < 0.001$.

Table S4. Results from linear mixed-effects regression models: Two cross-level interactions (student-level growth mindsets × social mobility index and student-level growth mindsets × educational mobility)

	Math			Science			Reading		
Variable	*b*	SE b	***β***	*b*	SE b	***β***	*b*	SE b	***β***
(Model C)									
Student-level variables									
GM L1	8.74***	0.98	0.08	11.23***	1.13	0.10	12.41***	1.25	0.11
Grit	5.48***	0.68	0.06	5.98***	0.79	0.06	7.66***	0.96	0.08
Self-efficacy	2.50***	0.70	0.03	1.49*	0.74	0.02	0.99	0.79	0.01
Age	11.98***	1.74	0.04	11.00***	1.27	0.03	10.36***	1.31	0.03
Male	12.29***	1.07	0.07	5.65***	1.24	0.03	-20.96***	1.54	-0.11
Socio-economic status	19.04***	1.66	0.20	18.25***	1.50	0.19	17.35***	1.64	0.16
School-level variables									
GM L2	52.15***	6.90	0.16	56.59***	6.60	0.17	68.16***	6.67	0.20
Student-teacher ratio	0.78***	0.23	0.05	0.73***	0.23	0.04	0.88**	0.29	0.05
Shortage of school resources	-3.37***	0.72	-0.03	-2.96***	0.82	-0.03	-3.53***	1.10	-0.03
Proportion of teachers qualified	5.89*	2.48	0.02	6.56**	2.47	0.02	7.90**	2.58	0.02
Learning-hindering behaviours	-10.08***	1.00	-0.10	-9.60***	1.10	-0.09	-10.43***	1.20	-0.09
Country-level variables									
GM L3	-29.06	36.22	-0.06	-13.17	29.10	-0.02	6.22	33.93	0.01
Educational mobility	0.40	0.30	0.05	0.32	0.26	0.04	0.38	0.23	0.04
Social mobility index	2.08	1.32	0.17	2.64*	1.07	0.21	1.28	1.17	0.10
Gini index	0.17	1.80	0.01	1.42	1.16	0.08	0.63	1.15	0.03
GDP per capita	-0.03	0.32	-0.01	-0.13	0.28	-0.03	0.25	0.30	0.05
Educational expenditure	0.95	1.40	0.03	0.56	1.13	0.02	0.95	1.16	0.03
Cross-level interaction									
GM L1 × social mobility index	0.08	0.12	0.01	0.15	0.12	0.01	0.11	0.14	0.01
GM L1 × educational mobility	0.22*	0.09	0.02	0.29**	0.11	0.03	0.29**	0.11	0.03
Intercept	497.98	3.55		499.31	3.09		498.26	3.02	

Values are unstandardized (*b*) and standardized coefficients with standard errors. GM, growth mindsets - L1,2,3 differentiates student, school, and country level of measurement. *P* values: *$P < 0.05$, **$P < 0.01$, ***$P < 0.001$.

Table S5. Results from linear mixed-effects regression models: Two cross-level interactions (student-level growth mindsets × GINI and student-level growth mindsets × educational mobility)

	Math			Science			Reading		
Variable	*b*	SE b	***β***	*b*	SE b	***β***	*b*	SE b	***β***
(Model D)									
Student-level variables									
GM L1	8.72***	0.97	0.08	11.22***	1.13	0.10	12.40***	1.22	0.11
Grit	5.48***	0.68	0.06	5.98***	0.79	0.06	7.66***	0.96	0.08
Self-efficacy	2.50***	0.70	0.03	1.49*	0.74	0.02	1.00	0.80	0.01
Age	11.98***	1.74	0.04	10.99***	1.27	0.03	10.35***	1.31	0.03
Male	12.29***	1.07	0.07	5.65***	1.24	0.03	-20.96***	1.54	-0.11
Socio-economic status	19.04***	1.66	0.20	18.25***	1.50	0.19	17.35***	1.64	0.16
School-level variables									
GM L2	52.15***	6.89	0.16	56.58***	6.60	0.17	68.15***	6.67	0.20
Student-teacher ratio	0.78***	0.23	0.05	0.73***	0.23	0.04	0.88**	0.29	0.05
Shortage of school resources	-3.37***	0.72	-0.03	-2.96***	0.82	-0.03	-3.53***	1.10	-0.03
Proportion of teachers qualified	5.89*	2.48	0.02	6.56**	2.47	0.02	7.90**	2.58	0.02
Learning-hindering behaviours	-10.08***	1.00	-0.10	-9.60***	1.10	-0.09	-10.43***	1.21	-0.09
Country-level variables									
GM L3	-29.37	36.24	-0.06	-13.04	29.09	-0.02	6.15	33.94	0.01
Educational mobility	0.40	0.30	0.05	0.32	0.26	0.04	0.38	0.23	0.04
Social mobility index	2.09	1.32	0.17	2.63*	1.07	0.21	1.28	1.17	0.10
Gini index	0.18	1.80	0.01	1.42	1.16	0.08	0.63	1.15	0.03
GDP per capita	-0.03	0.32	-0.01	-0.13	0.28	-0.03	0.24	0.30	0.05
Educational expenditure	0.94	1.40	0.03	0.57	1.13	0.02	0.94	1.16	0.03
Cross-level interaction									
GM L1 × Gini index	0.14	0.20	0.01	0.15	0.20	0.01	0.21	0.22	0.01
GM L1 × educational mobility	0.22*	0.10	0.02	0.30*	0.12	0.03	0.29*	0.12	0.03
Intercept	497.98	3.55		499.31	3.09		498.26	3.03	

Values are unstandardized (*b*) and standardized coefficients with standard errors. GM, growth mindsets - L1,2,3 differentiates student, school, and country level of measurement. *P* values: **P* < 0.05, ***P* < 0.01, ****P* < 0.001.

Table S6. Results from linear mixed-effects regression models: Three-way cross-level interaction (student-level growth mindsets × student-level socioeconomic status × educational mobility)

	Math			Science			Reading		
Variable	*b*	SE b	***β***	*b*	SE b	***β***	*b*	SE b	***β***
(Model E)									
Student-level variables									
GM L1	8.77***	0.97	0.08	10.90***	1.09	0.10	12.39***	1.24	0.11
Grit	5.41***	0.69	0.06	5.60***	0.75	0.06	7.56***	0.95	0.08
Self-efficacy	2.53***	0.70	0.03	1.77*	0.70	0.02	1.03	0.79	0.01
Age	11.81***	1.69	0.04	10.59***	1.19	0.03	10.24***	1.29	0.03
Male	12.54***	1.09	0.07	5.99***	1.20	0.03	-20.77***	1.52	-0.10
SES L1	16.19***	1.21	0.14	15.97***	1.23	0.13	14.91***	1.21	0.11
School-level variables									
GM L2	29.44***	3.86	0.09	34.81***	4.21	0.11	39.00***	5.23	0.12
Student-teacher ratio	0.30	0.22	0.02	0.29	0.22	0.02	0.51*	0.22	0.03
Shortage of school resources	0.24	0.47	0.00	0.61	0.47	0.01	0.26	0.59	0.00
Proportion of teachers qualified	4.15	2.23	0.01	5.01*	2.47	0.02	4.96	2.75	0.02
Learning-hindering behaviours	-4.19***	0.84	-0.04	-4.03***	0.91	-0.04	-4.42***	0.92	-0.04
SES L2	69.63***	5.56	0.39	67.01***	6.24	0.37	76.27***	4.91	0.40
Country-level variables									
GM L3	-32.11	34.26	-0.06	-16.46	26.27	-0.03	3.73	31.82	0.01
Educational mobility (**EM**)	0.90*	0.40	0.10	0.90***	0.24	0.10	0.79***	0.23	0.09
Social mobility index	3.48**	1.17	0.28	4.12***	0.68	0.33	2.46**	0.90	0.19
Gini index	0.16	1.61	0.01	1.36	0.78	0.07	0.58	0.85	0.03
GDP per capita	-0.01	0.26	-0.00	-0.09	0.22	-0.02	0.26	0.24	0.05
Educational expenditure	0.60	1.13	0.02	0.27	0.97	0.01	0.58	0.99	0.02
SES L3	-32.12*	14.82	-0.11	-40.58***	8.80	-0.13	-25.09**	9.53	-0.08
Cross-level interactions									
GM L1 × SES L1	-1.60	0.91	-0.01	-1.66***	0.30	-0.01	-1.74***	0.45	-0.01
GM L1 × EM	0.22**	0.09	0.02	0.31**	0.11	0.03	0.29**	0.11	0.03
SES L1 × EM	0.20	0.12	0.02	0.29*	0.14	0.02	0.29*	0.12	0.02
GM L1 × SES L1 × EM	-0.07	0.04	-0.00	-0.05	0.03	-0.00	-0.02	0.03	-0.00
Intercept	500.66	3.32		501.48	2.44		501.12	2.65	

Values are unstandardized (*b*) and standardized coefficients with standard errors. GM, growth mindsets; SES, socioeconomic status; EM, educational mobility - L1,2,3 differentiates student, school, and country level of measurement. *P* values: $*P < 0.05$, $**P < 0.01$, $***P < 0.001$.

Table S7. Supplemental results for cross-level interactions (student-level growth mindsets × educational mobility) and simple slopes across different SES backgrounds

	Math			Science			Reading		
Interaction at each level of SES	*b*	SE b	***β***	*b*	SE b	***β***	*b*	SE b	***β***
GM L1 × educational mobility									
Low SES (-1 SD)	0.27**	0.09	0.03	0.35**	0.11	0.03	0.31**	0.12	0.03
High SES (+1 SD)	0.17	0.09	0.02	0.27**	0.10	0.03	0.28**	0.10	0.03

Simple slopes of GM L1 predicting performance	Math			Science			Reading		
	b	SE b	***β***	*b*	SE b	***β***	*b*	SE b	***β***
High educational mobility (+1 SD)									
Low SES (-1 SD)	12.93***	1.81	0.12	15.87***	1.92	0.15	17.01***	2.20	0.15
High SES (+1 SD)	9.39***	1.65	0.09	12.51***	1.74	0.12	14.04***	1.74	0.12
Low educational mobility (-1 SD)									
Low SES (-1 SD)	7.08***	1.38	0.07	8.50***	1.36	0.08	10.46***	1.47	0.09
High SES (+1 SD)	5.68***	1.28	0.05	6.73***	1.25	0.06	8.07***	1.42	0.07

Values are unstandardized (*b*) and standardized coefficients with standard errors. GM, growth mindsets - L1 represents the student level measure. *P* values: $^*P < 0.05$, $^{**}P < 0.01$, $^{***}P < 0.001$.

SI Materials and Methods (Study 2)

2A. Power analysis. An *a priori* power analysis was conducted to determine the sample size needed to detect the primary confirmatory test: the interaction between growth mindsets and environment condition or the mindsets × condition (1st contrast). To be on the conservative side, we aimed to detect a small effect (f^2 = 0.02; f^2_{small} = 0.02, f^2_{medium} = 0.15, f^2_{large} = 0.35; 20) with at least 95% power. Using G*Power (21), it was determined that the minimum sample size needed was 652 (Table S8).

Table S8. Power analysis for Study 2

Input	
Effect size f^2	0.02
α error probability	0.05
Power (1 – β error probability)	0.95
Number of tested predictors	1
Total number of predictors	3
Output	
Non-centrality parameter λ	13.04
Critical F	3.86
Numerator df	1
Denominator df	648
Total sample size	652
Actual power	0.95

Power analysis for the growth mindsets × condition (1st contrast) interaction. A small effect size of f^2 = 0.02 was specified, and a sample size of 652 was needed to achieve 95% power.

Hence, we formulated a data collection plan: 1) we would collect data in blocks according to university semesters, 2) we collected as many data as we could in each semester, and 3) we would stop the data collection if 652 was met; if not, data collection in another semester would be planned. Eventually, we spent three semesters to collect data from 744 participants.

Sensitivity power analyses showed that the final sample (n = 744) was large enough to detect f^2 = 0.018 at 95% power and f^2 = 0.011 at 80% power, the latter of which is almost half of the small effect prescribed by Cohen (20). Further sensitivity power analyses were conducted to examine the effect sizes that our two exploratory tests: mindsets × condition (2nd contrast) and mindsets × condition (3rd contrast), could detect. As both tests pertained to half of the total participants (n = 372), they were still large enough to detect f^2 = 0.035 at 95% power and f^2 = 0.021 at 80% power. In sum, our final sample had more than adequate power to conduct confirmatory tests to detect small effects and adequate power to detect small and small-to-medium effects for the intended exploratory tests.

2B. Overview of Trait Variables. All participants completed a self-report questionnaire measuring their growth mindsets, grit, and self-esteem in the first session. In each scale, all negatively worded items were reverse scored such that a higher score on the measure meant having more of a growth mindsets, being grittier, or having higher self-esteem.

Growth mindsets of intelligence. Participants answered eight-items adapted from Dweck's original mindset scale (3). Items include, "Your intelligence is something about you that you can't change very much," "You can learn new things, but you can't really change your basic intelligence," "No matter who you are, you can significantly change your intelligence level," and "No matter how much intelligence you have, you can always change it quite a bit." All items were on a six-point Likert scale, ranging from strongly disagree to strongly agree (α = 0.91).

Grit. Participants responded to 12-items measuring one's perseverance of effort and consistency of interests over time (22). Items that measure the former include, "I have achieved a goal that took years of work" and "Setbacks don't discourage me". Examples of items measuring the latter are "New ideas and new projects sometimes distract me from previous ones" and "I become interested in new pursuits every few months." Items were rated on a five-point scale from *not at all like me* to *very much like me* (α = 0.77 for perseverance of effort; α = 0.81 for consistency of interests).

Self-esteem. Participants answered 10-items from the Rosenberg Self-Esteem scale (23), which include "On the whole, I am satisfied with myself," "I feel that I'm a person of worth, at least on an equal plane with others," "At times, I think I am no good at all," and "I certainly feel useless at times." All items were on a four-point Likert scale ranging from strongly disagree to strongly agree (α = 0.77).

Correlations. Growth mindsets of intelligence correlated significantly with perseverance of effort and self-esteem, but not consistency of interests (Table S9).

Table S9. Correlations Between Trait Variables (Study 2; *n* = 744)

Variables	1	2	3	4
1. GM	-			
2. Grit PoE	.108**	-		
3. Grit CoI	-.039	.272***	-	
4. Self-esteem	.149***	.413***	.163***	-

Values are Pearson correlation coefficients (*r*). GM refers to growth mindsets of intelligence. Grit PoE and Grit CoI refer respectively to the perseverance of effort and consistency of interests subsets of the grit construct (22). *P* values: **P* < 0.05, ***P* < 0.01, ****P* < 0.001.

2C. Study Design Specifics. The study was programmed on Psytoolkit, an online software for designing and delivering psychological experiments via a weblink (24, 25). This section will provide additional information on the study design to augment the methods described in the main text. The four sessions took an average of 1.5 hours to complete, and participants were reimbursed 15 SGD for their time.

Intelligence framing. To frame change blindness as a measure of intelligence, we provided participants with the following short passage at the beginning of the study:

Perceptiveness to change is an aspect of our intelligence that involves an individual's capacity to detect changes quickly in the environment. Not surprisingly, it is closely associated with one's situational awareness – the ability to quickly perceive and comprehend everything going on in a situation. Past research has found that individuals who score high on these measures tend to possess greater intrapersonal and interpersonal skills [citation], have their colleagues and employers rely on them more [citation], and hold higher office positions in their company or workplace [citation]. One likely reason is because being aware of small, negative but consequential changes in your surroundings allows you to react promptly and appropriately before the situation escalates for the worse.

Flicker task. Images used in the flicker task was provided by the Visual Attention Lab at Harvard Medical School (26). The database is public and can be accessed through their website (https://search.bwh.harvard.edu/new/CBDatabase.html). It offers a variety of change blindness scenarios by manipulating different aspects between two scenes, such as colour changes, shadow appearances, mirrored items, and missing items. To keep the task consistent throughout the sessions, we opted to use scenes with missing items as they made up the majority of images in the database. We used the *Main CB Database* and the *Additional CB images* supplementary pack, which offered a total of 180 unique scenes. As our study required 183 trials, inclusive of a fixed set of 3 practice trials before each assessment, 3 scenes featured in the 1st session were mirrored (or flipped horizontally) and used in the 4th session. This ensured that no trial throughout the study was exactly the same.

Participants were given the following instructions for the task:

On each trial, you will be presented with a pair of images alternating quickly between each other. While the images feature the same scene, an object is missing from one of them. Your task is to find this object as quickly as possible. When you detect the change (i.e., missing object), press the spacebar. You will be shown the time taken for that trial, followed by a static image of that scene. Using your mouse, click on the object that "changed" between the two images. Once done, the program will inform you on whether you were correct or wrong, before starting the next trial immediately. If you are unable to detect the change after 60 seconds has passed, the trial will time out, and you will be considered to have gotten the trial incorrect. You will be evaluated on both speed (i.e., number of seconds) and accuracy (i.e., finding the object).

Mobility Paradigm. Participants were introduced to the high or low mobility nature of the program, depending on the condition they were assigned to. This was conveyed through a visual diagram shown to all participants at the start of every session (Fig. S2).

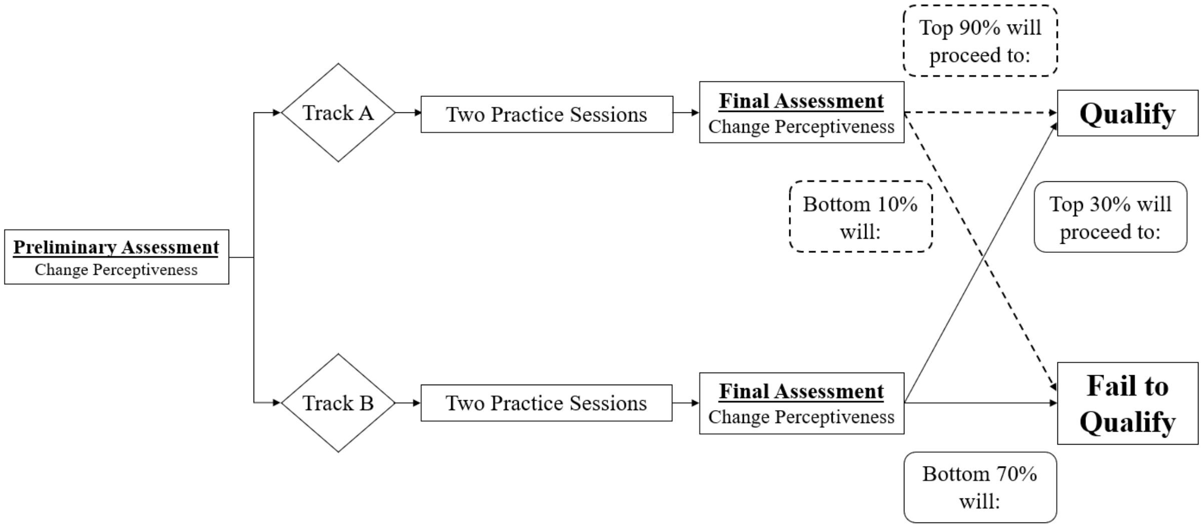


Figure S2. Visual diagram outlining the structure of the program for participants in the high-mobility condition (Study 2). In the low-mobility condition, the chance of qualifying was adjusted to **99%** and **3%** for upper track A and lower track B participants, respectively. The preliminary assessment, two practice sessions, final assessment make up the 4 sessions of the longitudinal study.

The diagram was accompanied with the following instruction in the initial assessment; participants were shown one set of percentages [in brackets] depending on whether they were in the high or low mobility condition:

Your performance on today's preliminary assessment will be evaluated against last year's cohort of participant scores, to which you will be assigned to one of two tracks. Being in Track A indicates that you are at a level of competency similar to those who managed to qualify last year. Conversely, being in Track B indicates that based on last year's scores, your level of competency would not be sufficient to qualify you. Regardless of the Track you are assigned to, the next two practice sessions will allow you to practice before the final assessment which will determine, based on your performance, whether or not you qualify. For participants in Track A, the top [90%/99%] will qualify, while the bottom [10%/1%] will not. For participants in Track B, only the top [30%/3%] will qualify, while the bottom [70%/97%] will not.

A short quiz on the diagram was given during the 1st and 4th sessions to ensure that they understood and did not forget their likelihood of qualifying.

2D. Analyses. Moderation and moderated mediation analyses for this study were conducted using the SPSS PROCESS macro (27). The results reported in the main text assumed that incomplete responses (not participating in the practice sessions and/or the final assessment) were indicative of participants' motivation to disengage in the learning environment. Hence, we replaced 1) absence in practices with zero practice time and zero practice attempts, and 2) absence in the final assessment with participants' initial assessment time and a disengagement penalty (+1 SE). This way, the results reported in the main text represented all the participants (N = 744) and adhered to the intent-to-treat principle. The parameter estimates for these models utilizing the full sample of participants are presented in Tables S10 to S14. We also repeated the analyses with an alternative index of growth mindsets with just the items endorsing fixed mindsets (reverse-scored), α = .89 in keeping with Study 1 and past research (28–30). The results remained the same (Tables S15 to S19).

Dataset and syntax for the main analyses can be found at https://doi.org/10.17605/OSF.IO/ZYV89

Analyses on participants with completed responses only. Here, we report results based only on complete responses to demonstrate that our conclusions hold regardless of our analytical choices. The same analyses reported in the paper were repeated here on a smaller sample after listwise exclusion. Again, we treated the experimental conditions as one factor with 4 levels, and coded it with three orthogonal contrasts:

1) 1st contrast (0.5, 0.5, -0.5, -0.5): the high-mobility condition vs. the low-mobility condition;
2) 2nd contrast (1, -1, 0, 0): the lower-track vs. the upper-track in the high-mobility condition;
3) 3rd contrast (0, 0, 1, -1): the lower-track vs. the upper-track in the low-mobility condition.

Practice engagement. To test the effect of the moderating role of conditions on the effect of mindsets, the mindsets × condition model was conducted on 682 participants who have completed both practice sessions.

Consistent with the results in the paper, we observed a significant mindsets × condition (1st contrast) interaction, b = 0.23; 95% CI = 0.06, 0.40; SE = 0.09; β = 0.20; $t(671)$ = 2.61, P = 0.0094, and a significant mindsets × condition (2nd contrast) interaction, b = 0.12; 95% CI = 0.01, 0.23; SE = 0.06; β = 0.11; $t(671)$ = 2.14; P = 0.0329. That is, growth mindsets positively predicted learning behavior in the high- but not low- mobility environment; this effect was primarily driven by disadvantaged learners.

Indeed, growth mindsets positively predicted practice engagement only in the high-mobility-lower-track condition, b = 0.30; 95% CI = 0.13, 0.46; SE = 0.07; β = 0.26; $t(671)$ = 3.51; P = 0.0005. One-unit increase in growth mindsets corresponds to 106s more in practice time (M = 498s, SD = 347s) or 9.63 more trials attempted (M = 58.6, SD = 37.1). Growth mindsets had no effect on practice engagement in any other conditions, ts < 1 (Fig. S3).

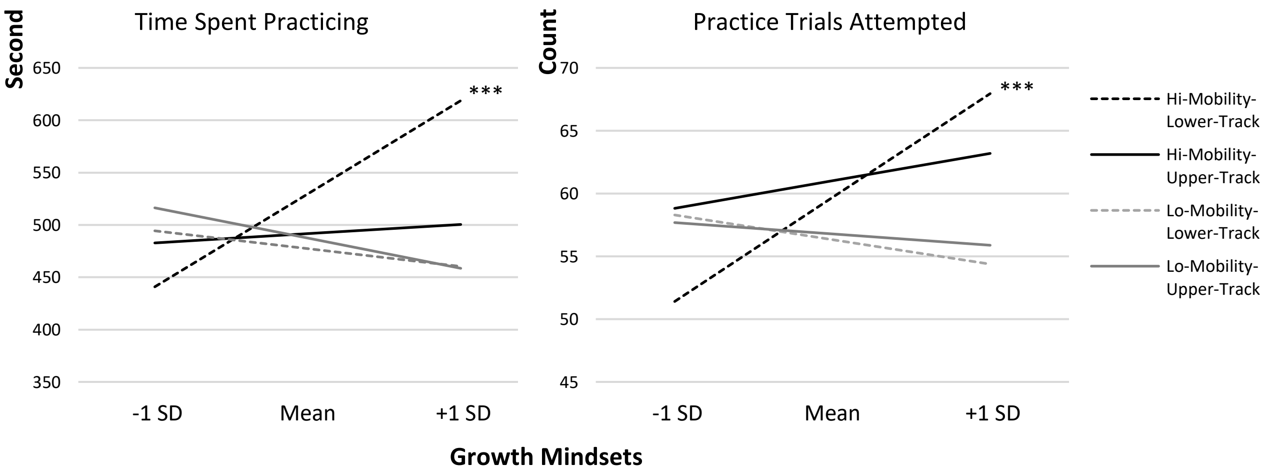
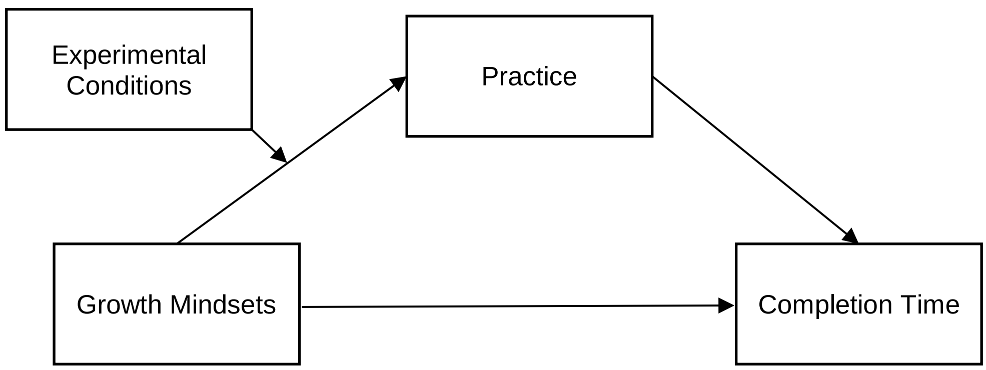


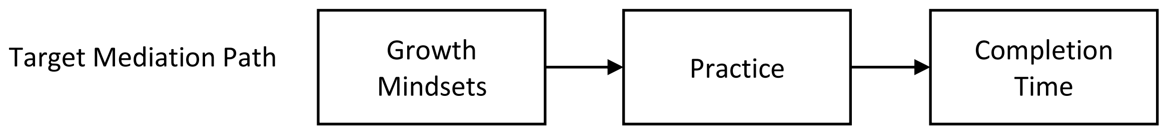
Figure S3. Practice engagement with growth mindsets by experimental conditions (Study 2). The left panel shows the total time spent on practice, and the right panel shows the total number of practice trials attempted. Black lines represent high-mobility environments, and grey lines represent low-mobility environments. Dashed lines represent lower-track conditions, and solid lines represent upper-track conditions. Main analysis was conducted on the computed average of the standardized values of total time and trials attempted. Analyses on the two separate indices yielded the same pattern of results. *P* values: **P* < .05, ***P* < .01, ****P* < 0.001.

Downstream consequences of practice engagement. To test the downstream consequences of the effect of the mindsets × condition interaction on practice, we redid the analysis on 630 participants who completed all four sessions.

The same moderated mediation model (Fig. S4) was conducted. Consistent with the main paper, the target mediation pathway (mindsets → practice engagement → final performance) was significant only in the high-mobility lower-track condition, b = -7.18; 95% CI = -12.72, -2.27; β = -0.07; bootstrap SE = 2.64.

Most importantly, the index of moderated mediation with condition (1st contrast), which is our theoretical focus, b = -6.40; 95% CI = -12.07, -1.59; β = -0.05; bootstrap SE = 2.70, was significant. That is, growth mindsets improved performance via practice only in the high- but not low-mobility environment.





Experimental Conditions	Tests of Target Mediation
High-Mobility-Lower-Track	b = -7.18, 95% CI [-12.72, -2.27], β = -.07, SE = 2.64
High-Mobility-Upper-Track	b = -1.87, 95% CI [-6.74, 2.63], β = -.01, SE = 2.328
Low-Mobility-Lower-Track	b = 2.27, 95% CI [-2.44, 6.85], β = .01, SE = 2.344
Low-Mobility-Upper-Track	b = 1.48, 95% CI [-3.83, 7.31], β = .01, SE = 2.804

Figure S4. The moderated meditation analysis (Study 2). Top panel: The moderated mediation model. Bottom panel: the target mediation path tested in each of the experimental conditions. Performance was measured by completion time, with shorter time representing better performance. Significant pathways are represented with confidence intervals that exclude 0.

Supplemental analysis on total effect of mindsets × condition on performance. To test the total effect of the mindsets × condition interaction on performance, we redid the analysis on 630 participants who completed all four sessions. The same pattern reported in the main text was observed.

In the high-mobility environment, growth mindsets did not have an overall predictability on performance in the lower-track condition, $t < 1$, but significantly predicted better performance (i.e., shorter time) in the upper-track condition, $b = -25.84$; 95% CI = -44.91, -6.68; $\beta = -0.15$; SE = 9.71; $t(618) = -2.66$; $P = 0.0080$.

In the low mobility environment, there was no effect of growth mindsets, both *t*s < 1. Instead, the initial advantage manipulation predominantly predicted performance. Participants in the lower track performed worse (i.e., longer time) than those in the upper track, $b = 15.57$; 95% CI = 8.77, 30.27; $\beta = 0.11$; SE = 7.48; $t(618) = 2.08$; $P = 0.0378$.

Overall, the analyses here support the same inferences reported in the main paper. In the high mobility environment, while the disadvantaged learners benefited from growth mindsets in terms of increased learning behavior, the advantaged learners seemed to benefit directly in terms of performance, revealing divergent ways through which growth mindsets facilitates academic achievement. In the low mobility environment, in which growth mindsets did not guide learners' behavior, the initial inequality, which was created by random assignment, perpetuated till the end of the study.

Table S10. Results from moderation analysis: Growth mindsets × condition predicting practice engagement (in seconds; *n* = 744)

Variable	*b*	95% CI Lower	95% CI Upper	*B*	SE	*t*	*P*
Key variables							
GM	0.07	-0.01	0.16	0.06	0.04	1.74	.0825
1st contrast	-0.02	-0.16	0.13	-0.02	0.07	-0.22	.8256
2nd contrast	-0.01	-0.11	0.09	-0.01	0.05	-0.13	.8950
3rd contrast	-0.00	-0.10	0.10	-0.00	0.05	-0.00	.9973
GM × 1st contrast	0.27	0.11	0.43	0.23	0.08	3.27	.0011
GM × 2nd contrast	0.15	0.05	0.26	0.13	0.05	2.81	.0052
GM × 3rd contrast	0.01	-0.12	0.13	0.01	0.06	0.14	.8897
Covariates							
Grit PoE	-0.09	-0.22	0.04	-0.06	0.07	-1.40	.1629
Grit CoI	-0.04	-0.15	0.07	-0.03	0.05	-0.72	.4711
Self-esteem	-0.11	-0.30	0.09	-0.04	0.10	-1.09	.2767

Coefficients shown here correspond to the results reported in the main text. Values are unstandardized (*b*) and standardized coefficients (*β)* with standard errors and 95% confidence intervals. GM refers to growth mindsets of intelligence. Grit PoE and Grit CoI refer respectively to the perseverance of effort and consistency of interests subsets of the grit construct (22). The 1st contrast compares between the high- and low-mobility conditions. The 2nd and 3rd contrast compares between the upper and lower tracks, within the high- and low-mobility conditions respectively.

Table S11. Conditional simple slope effects of growth mindsets predicting practice engagement (in seconds; *n* = 744)

Condition	*b*	95% CI Lower	95% CI Upper	*β*	SE	*t*	*P*
High mobility, Lower track	0.36	0.22	0.50	0.31	0.07	4.96	.0000
High mobility, Upper track	0.06	-0.10	0.21	0.05	0.08	0.73	.4645
Low mobility, Lower track	-0.05	-0.21	0.11	-0.05	0.08	-0.65	.5142
Low mobility, Upper track	-0.07	-0.26	0.12	-0.06	0.10	-0.73	.4659

Coefficients shown here correspond to the results reported in the main text. Values are unstandardized (*b*) and standardized coefficients (*β)* with standard errors and 95% confidence intervals.

Table S12. Results from moderated mediation analysis: Practice engagement mediating the relationship between growth mindsets × condition and final performance (controlling for initial performance; *n* = 744)

Variable	*b*	95% CI Lower	95% CI Upper	*β*	SE	*t*	*P*
MV: Practice engagement							
Key variables							
GM	0.07	-0.01	0.15	0.06	0.04	1.70	.0902
1st contrast	-0.02	-0.16	0.12	-0.02	0.07	-0.25	.8002
2nd contrast	-0.01	-0.10	0.09	-0.01	0.05	-0.11	.9102
3rd contrast	0.00	-0.10	0.10	0.00	0.05	0.06	.9518
GM × 1st contrast	0.27	0.11	0.43	0.23	0.08	3.27	.0011
GM × 2nd contrast	0.15	0.05	0.26	0.13	0.05	2.84	.0046
GM × 3rd contrast	0.01	-0.12	0.13	0.01	0.06	0.13	.8994
Covariates							
Initial performance	-0.00	-0.00	0.00	-0.03	0.00	-0.62	.5370
Grit PoE	-0.09	-0.22	0.04	-0.06	0.07	-1.35	.1761
Grit CoI	-0.04	-0.14	0.07	-0.03	0.05	-0.67	.5009
Self-esteem	-0.11	-0.31	0.08	-0.05	0.10	-1.12	.2632
DV: Final performance							
Key variables							
GM	-7.22	-17.51	3.07	-0.04	5.24	-1.38	.1686
Practice engagement	-41.91	-51.50	-32.32	-0.27	4.89	-8.58	.0000
Covariates							
Initial performance	0.60	0.50	0.69	0.56	0.05	12.43	.0000
Grit PoE	-2.95	-23.59	17.70	-0.01	10.52	-0.28	.7793
Grit CoI	2.09	-11.76	15.94	0.01	7.05	0.30	.7671
Self-esteem	12.45	-17.73	42.63	0.03	15.37	0.81	.4183

Conditional indirect effects at different levels of condition	*b*	95% CI Lower	95% CI Upper	*β*	Boot SE
High mobility, Lower track	-15.05	-22.09	-8.59	-0.08	3.42
High mobility, Upper track	-2.30	-9.03	4.21	-0.01	3.36
Low mobility, Lower track	2.36	-4.43	8.53	0.01	3.36
Low mobility, Upper track	3.03	-4.95	11.42	0.02	4.15

Indices of moderated mediation for each contrast	*b*	95% CI Lower	95% CI Upper	*β*	Boot SE
1st contrast	-11.37	-18.54	-4.37	-0.06	3.64
2st contrast	-6.38	-11.04	-2.00	-0.03	2.33
3st contrast	-0.34	-5.85	4.80	-0.00	2.67

Coefficients shown here correspond to the results reported in the main text. Values are unstandardized (*b*) and standardized coefficients (*β)* with standard errors and 95% confidence intervals. The percentile bootstrap confidence intervals for indirect effects were generated using 5,000 bootstrap samples. GM refers to growth mindsets of intelligence. Grit PoE and Grit CoI refer respectively to the perseverance of effort and consistency of interests subsets of the grit construct (22). The 1st contrast compares between the high- and low-mobility conditions. The 2nd and 3rd contrast compares between the upper and lower tracks, within the high- and low-mobility conditions respectively.

Table S13. Results from moderation analysis: Growth mindsets × condition predicting final performance (controlling for initial performance; *n* = 744)

Variable	*b*	95% CI Lower	95% CI Upper	*β*	SE	*t*	*P*
Key variables							
Mindsets	-9.65	-20.53	1.24	-0.05	5.55	-1.74	.0824
1st contrast	-1.45	-19.73	16.84	-0.01	9.31	-0.16	.8766
2nd contrast	5.59	-6.57	17.76	0.04	6.20	0.90	.3669
3rd contrast	18.28	4.62	31.94	0.12	6.96	2.63	.0088
Mindsets × 1st contrast	-14.83	-35.85	6.18	-0.08	10.70	-1.39	.1663
Mindsets × 2nd contrast	11.52	-2.20	25.24	0.06	6.99	1.65	.0990
Mindsets × 3rd contrast	-2.64	-18.21	12.93	-0.01	7.93	-0.33	.7389
Covariates							
Initial performance	0.60	0.50	0.69	0.56	0.05	12.26	.0000
Grit PoE	-0.22	-21.56	21.11	-0.00	10.87	-0.02	.9836
Grit CoI	4.46	-9.43	18.35	0.02	7.07	0.63	.5287
Self-esteem	16.21	-16.14	48.55	0.04	16.48	0.98	.3255

Coefficients shown here correspond to the results reported in the main text. Values are unstandardized (*b*) and standardized coefficients (*β*) with standard errors and 95% confidence intervals. GM refers to growth mindsets of intelligence. Grit PoE and Grit CoI refer respectively to the perseverance of effort and consistency of interests subsets of the grit construct (22). The 1st contrast compares between the high- and low-mobility conditions. The 2nd and 3rd contrast compares between the upper and lower tracks, within the high- and low-mobility conditions respectively.

Table S14. Conditional simple slope effects of growth mindsets predicting final performance (controlling for initial performance; *n* = 744)

Conditions	*b*	95% CI Lower	95% CI Upper	*β*	SE	*t*	*P*
High mobility, Lower track	-5.54	-25.52	14.43	-0.03	10.17	-0.55	.5860
High mobility, Upper track	-28.58	-47.18	-9.98	-0.16	9.47	-3.02	.0026
Low mobility, Lower track	4.87	-29.31	19.56	-0.03	12.45	-0.39	.6960
Low mobility, Upper track	0.42	-20.45	21.28	0.00	10.63	0.04	.9690

Coefficients shown here correspond to the results reported in the main text. Values are unstandardized (*b*) and standardized coefficients (*β*) with standard errors and 95% confidence intervals.

Table S15. Results from moderation analysis: Growth mindsets (only using items endorsing a fixed mindset) × condition predicting practice engagement (in seconds; *n* = 744)

Variable	*b*	95% CI Lower	95% CI Upper	*B*	SE	*t*	*P*
Key variables							
GM	0.10	0.03	0.17	0.10	0.04	2.71	.0069
1st contrast	-0.02	-0.16	0.12	-0.02	0.07	-0.27	.7879
2nd contrast	-0.01	-0.11	0.09	-0.01	0.05	-0.15	.8837
3rd contrast	-0.00	-0.10	0.10	-0.00	0.05	-0.04	.9645
GM × 1st contrast	0.21	0.07	0.35	0.21	0.07	2.93	.0034
GM × 2nd contrast	0.11	0.02	0.21	0.11	0.05	2.36	.0188
GM × 3rd contrast	-0.01	-0.12	0.09	-0.01	0.05	-0.24	.8093
Covariates							
Grit PoE	-0.09	-0.22	0.04	-0.06	0.07	-1.38	.1696
Grit CoI	-0.05	-0.15	0.06	-0.03	0.05	-0.83	.4046
Self-esteem	-0.11	-0.30	0.09	-0.04	0.10	-1.10	.2726

Coefficients shown here correspond to the results reported in the main text. Values are unstandardized (*b*) and standardized coefficients (*β)* with standard errors and 95% confidence intervals. GM refers to growth mindsets of intelligence. Grit PoE and Grit CoI refer respectively to the perseverance of effort and consistency of interests subsets of the grit construct (22). The 1st contrast compares between the high- and low-mobility conditions. The 2nd and 3rd contrast compares between the upper and lower tracks, within the high- and low-mobility conditions respectively.

Table S16. Conditional simple slope effects of growth mindsets (only using items endorsing a fixed mindset) predicting practice engagement (in seconds; *n* = 744)

Condition	*b*	95% CI Lower	95% CI Upper	*β*	SE	*t*	*P*
High mobility, Lower track	0.31	0.19	0.44	0.32	0.06	4.84	.0000
High mobility, Upper track	0.09	-0.05	0.23	0.09	0.07	1.24	.2155
Low mobility, Lower track	-0.02	-0.15	0.11	-0.02	0.07	-0.31	.7595
Low mobility, Upper track	0.00	-0.15	0.16	0.00	0.08	0.06	.9539

Coefficients shown here correspond to the results reported in the main text. Values are unstandardized (*b*) and standardized coefficients (*β)* with standard errors and 95% confidence intervals.

Table S17. Results from moderated mediation analysis: Practice engagement mediating the relationship between growth mindsets (only using items endorsing a fixed mindset) × condition and final performance (controlling for initial performance; *n* = 744)

Variable	*b*	95% CI Lower	95% CI Upper	*β*	SE	*t*	*P*
MV: Practice engagement							
Key variables							
GM	0.09	0.02	0.17	0.10	0.04	2.65	.0083
1st contrast	-0.02	-0.16	0.12	-0.02	0.07	-0.30	.7671
2nd contrast	-0.01	-0.10	0.09	-0.01	0.05	-0.13	.8967
3rd contrast	0.00	-0.10	0.10	0.00	0.05	0.01	.9914
GM × 1st contrast	0.21	0.07	0.35	0.21	0.07	2.93	.0035
GM × 2nd contrast	0.11	0.02	0.21	0.12	0.05	2.37	.0182
GM × 3rd contrast	-0.01	-0.12	0.09	-0.01	0.05	-0.24	.8101
Covariates							
Initial performance	-0.00	-0.00	0.00	-0.03	0.00	-0.53	.5946
Grit PoE	-0.09	-0.22	0.04	-0.06	0.07	-1.34	.1808
Grit CoI	-0.04	-0.15	0.06	-0.03	0.05	-0.79	.4286
Self-esteem	-0.11	-0.31	0.08	-0.05	0.10	-1.12	.2617
DV: Final performance							
Key variables							
GM	-6.10	-14.69	2.48	-0.04	4.37	-1.40	.1632
Practice engagement	-41.75	-51.35	-32.15	-0.27	4.89	-8.53	.0000
Covariates							
Initial performance	0.60	0.50	0.69	0.56	0.05	12.44	.0000
Grit PoE	-3.66	-24.53	17.20	-0.01	10.63	-0.34	.7305
Grit CoI	2.68	-11.01	16.38	0.01	6.97	0.38	.7005
Self-esteem	12.33	-17.70	42.37	0.03	15.30	0.81	.4204

Conditional indirect effects at different levels of condition	Boot *b*	95% CI Lower	95% CI Upper	*β*	Boot SE
High mobility, Lower track	-13.09	-19.33	-7.17	-0.08	3.06
High mobility, Upper track	-3.56	-9.55	2.33	-0.02	2.98
Low mobility, Lower track	0.93	-4.65	6.45	0.01	2.77
Low mobility, Upper track	-0.13	-6.69	6.32	-0.00	3.30

Indices of moderated mediation for each contrast	Boot *b*	95% CI Lower	95% CI Upper	*β*	Boot SE
1st contrast	-8.73	-14.84	-2.95	-0.06	3.06
2st contrast	-4.76	-8.94	-0.71	-0.03	2.06
3st contrast	0.53	-3.72	4.67	0.00	2.16

Coefficients shown here correspond to the results reported in the main text. Values are unstandardized (*b*) and standardized coefficients (*β*) with standard errors and 95% confidence intervals. The percentile bootstrap confidence intervals for indirect effects were generated using 5,000 bootstrap samples. GM refers to growth mindsets of intelligence. Grit PoE and Grit CoI refer respectively to the perseverance of effort and consistency of interests subsets of the grit construct (22). The 1st contrast compares between the high- and low-mobility conditions. The 2nd and 3rd contrast compares between the upper and lower tracks, within the high- and low-mobility conditions respectively.

Table S18. Results from moderation analysis: Growth mindsets (only using items endorsing a fixed mindset) × condition predicting final performance (controlling for initial performance; *n* = 744)

Variable	*b*	95% CI Lower	95% CI Upper	*β*	SE	*t*	*P*
Key variables							
Mindsets	-9.38	-18.64	-0.13	-0.06	4.71	-1.99	.0468
1st contrast	-1.11	-19.38	17.15	-0.01	9.30	-0.12	.9046
2nd contrast	5.47	-6.73	17.67	0.04	6.22	0.88	.3792
3rd contrast	18.20	4.62	31.78	0.12	6.92	2.63	.0087
Mindsets × 1st contrast	-12.66	-30.68	5.37	-0.08	9.18	-1.38	.1684
Mindsets × 2nd contrast	6.65	-5.11	18.41	0.04	5.99	1.11	.2671
Mindsets × 3rd contrast	-5.15	-18.74	8.44	-0.03	6.92	-0.74	.4570
Covariates							
Initial performance	0.59	0.50	0.69	0.56	0.05	12.28	.0000
Grit PoE	-0.89	-22.58	20.80	-0.00	11.05	-0.08	.9358
Grit CoI	5.05	-8.64	18.74	0.02	6.97	0.72	.4693
Self-esteem	17.13	-15.09	49.35	0.04	16.41	1.04	.2970

Coefficients shown here correspond to the results reported in the main text. Values are unstandardized (*b*) and standardized coefficients (*β*) with standard errors and 95% confidence intervals. GM refers to growth mindsets of intelligence. Grit PoE and Grit CoI refer respectively to the perseverance of effort and consistency of interests subsets of the grit construct (22). The 1st contrast compares between the high- and low-mobility conditions. The 2nd and 3rd contrast compares between the upper and lower tracks, within the high- and low-mobility conditions respectively.

Table S19. Conditional simple slope effects of growth mindsets (only using items endorsing a fixed mindset) predicting final performance (controlling for initial performance; *n* = 744)

Conditions	*b*	95% CI Lower	95% CI Upper	*β*	SE	*t*	*P*
High mobility, Lower track	-9.06	-26.68	8.56	-0.06	8.97	-1.01	.3130
High mobility, Upper track	-22.36	-37.69	-7.04	-0.14	7.81	-2.87	.0043
Low mobility, Lower track	-8.21	-29.51	13.10	-0.05	10.85	-0.76	.4497
Low mobility, Upper track	2.10	-15.63	19.82	0.01	9.03	0.23	.8164

Coefficients shown here correspond to the results reported in the main text. Values are unstandardized (*b*) and standardized coefficients (*β*) with standard errors and 95% confidence intervals.

SI Materials and Methods (Pilot Studies)

3A. Pilot Study A.

Design specifics. A total of 120 American participants were recruited from Amazon mTurk and randomly assigned to either a high (n = 61) or low mobility (n = 59) condition. In both conditions, participants read a short passage about an unfamiliar country (i.e., Malta) and information about its educational mobility. In the high (or low) mobility condition, participants were told that the country's educational mobility index was 36.6% (or 4.5%), and that this was substantially higher (or lower) than the average of 20.6% achieved in developed countries. These percentages were derived from OECD's 2018 educational mobility index (1): 20.6% was the actual average, and 36.6% and 4.5% correspond to the degree of mobility at +1.5 and -1.5 standard deviations from the mean, respectively. After reading the passage, participants were asked to imagine themselves as a typical student in that country, and respond to four-items measuring how instrumental active learning would be in helping them achieve academic success. Items included were "As a student in Malta, persevering hard in my studies will do little to increase my chances of completing tertiary education," "As a student in Malta, there is little reason to challenge myself in my studies as it would not improve my academic performance by much," "As a student in Malta, no matter how much I persevere in my studies, it will barely improve my academic performance," and "As a student in Malta, it is very difficult to develop my academic abilities even if I constantly challenge myself." A seven-point Likert scale ranging from "strongly disagree" to "strongly agree" was used. Higher scores indicated that active learning was perceived to be less instrumental in achieving academic success (α = .87). Participants took an average of 7 mins to complete the study, and were reimbursed 0.70 USD for their time.

Passage shown to participants:

Educational mobility focuses on the extent to which students from low-education households can overcome challenges to succeed in academic settings. Low-education households, comprising parents who did not complete Grade 12 (upper secondary), tend to be economically disadvantaged. Having less income often translates to fewer educational resources and learning materials at home. In addition, students from such families are also less likely to have access to early education, which further increases the barriers to academic achievement. Educational mobility therefore measures the extent to which countries have taken steps to support these disadvantaged students in their learning. It is reflected by the percentage of students from low-education households who were able to successfully graduate from tertiary education (college or university).

*We would now like you to think about the academic experience of a student in the country of Malta. In OECD's 2018 Educational Mobility Index, it was reported that in Malta, **36.6% (or 4.5%)** of students from low-education households manage to complete tertiary education (college or university). This is substantially **higher (or lower)** than the average of **20.6%** achieved in developed countries. What does this **high (or low)** educational mobility mean in everyday life? It means that it is relatively quite **common (or rare)** to hear about or witness students from low education households enter college and eventually graduate from one.*

Take a moment to imagine how students in Malta would think about their chances of finishing college.

Supplemental parameter estimates. Results reported in the main text showed that participants in the high mobility condition (M = 2.02, SD = 0.87) perceived active learning to be more instrumental in achieving academic success compared to those in the low mobility condition (M = 3.48, SD = 1.26).

3B. Pilot Study B.

Design specifics. In this study, we recruited 125 Singaporean undergraduates and utilized the same initial cover story and mobility paradigm featured in Study 2. Participants were randomly assigned to the high (n = 61) or low (n = 64) mobility condition and viewed the progression structure with percentages respective to the condition they were in (Fig S2). In the high mobility condition, the upper (i.e., Track A) and lower track (i.e., Track B) participants had around 90% and 30% chance of qualifying, respectively. In the low mobility condition, these percentages were adjusted to 99% and 3%. Participants then answered four-items adapted from Pilot Study A in measuring how instrumental active learning would be in improving one's ability to perceive change. Items included were "The progression system informed me that persevering hard on this task will do little to help me improve my performance", "The progression system informed me that there is little reason to challenge myself on this task as it would not improve my performance by much," "The progression system informed me that no matter how much I persevere on the task, it will barely improve my scores," and "The progression system informed me that it is very difficult to improve my change perceptiveness performance even if I constantly challenge myself." A seven-point Likert scale ranging from "strongly disagree" to "strongly agree" was used. Higher scores indicated that active learning was perceived to be less instrumental in improving one's ability to perceive change (α = .86). The study lasted an average of 15 mins, and all participants were reimbursed 2.50 SGD for their time.

Supplemental parameter estimates. Results reported in the main text showed that participants in the high mobility condition (M = 3.00, SD = 0.94) perceived active learning to be more instrumental in improving one's ability to perceive change compared to those in the low mobility condition (M = 3.43, SD = 1.28).

SI Additional Studies & Analyses

4. Does Educational Mobility Predict Mindsets?

Supplemental analyses on PISA. The ICCs on the PISA dataset revealed that the differences between countries accounted for 3.5% of the variance in growth mindsets of intelligence. As such, it is informative to examine if educational mobility predicts mindsets. We regressed growth mindsets on educational mobility in a three-level (students nested in schools nested in countries) multilevel regression. For this initial step, no covariates were added into the model. Educational mobility did not reliably predict growth mindsets, b = 0.00, SE = 0.00, β = 0.04, P = 0.140, and accounted for only 0.2% of the variability in growth mindsets. After adding all the student-, school-, and country-level covariates into the model, the relationship remained non-significant, b = -0.00, SE = 0.00, β = -0.01, P = 0.717. Above and beyond these covariates, educational mobility accounted for less than 0.1% of the variability in growth mindsets.

Pilot study for the experiment. To test if mobility had short-term effects on manipulating mindsets, we conducted a pilot study, adapting the methodology from the first session (preliminary assessment) of Study 2. A total of 162 Singaporean undergraduate students were recruited and randomly assigned to one of the four conditions, 2 (Mobility: High vs. Low) × 2 (Track: Upper vs. Lower) – fully between subjects. Using the same cover story, participants were informed that they were enrolling in a pilot program evaluating their "change perceptiveness", an aspect of intelligence that predicted positive life outcomes (see Section 2C). Those who qualified could be invited for well-paid follow-up experiments and attractive internships. In this session, they would complete an initial assessment which they were told, would assign them to an upper (i.e., Track A) or lower track (i.e., Track B) based on their performance. The tracks informed them of their likelihood of qualifying during the final assessment held on the 4th session. Participants in the high mobility condition were informed that, based on past data, the upper and lower track had a 90% and 30% chance to qualify, respectively. In the low mobility condition, the chances were 99% and 3% chance, respectively.

Upon completing the initial assessment and receiving their randomly assigned track, participants were asked to complete two mindsets scales. The first was a measure of growth mindsets of intelligence, comprising the original four fixed mindset endorsing items (α = 0.85; 3). We adapted these four items to create a second scale measuring growth mindsets of change perceptiveness (α = 0.81). Items included, "Your ability to detect changes quickly is something about you that you can't change very much," and "You have a certain amount of ability to detect changes quickly, and you can't really do much to change it." We acknowledged that even if no change in mindsets of general intelligence was observed, it was possible that growth mindsets about domain-specific aspects of intelligence, in this case change perceptiveness, could change. All items were on a six-point Likert scale, ranging from strongly disagree to strongly agree. In addition, item scores were reversed such that a higher score indicated more of a growth mindset of intelligence or change perceptiveness.

In predicting growth mindsets of intelligence, a two-way ANOVA revealed firstly, that the interaction between mobility and track was not statistically significant, $F(1, 158) = 0.61$, P = 0.436. The main effect of mobility, $F(1, 158) = 0.42$, P = 0.519, as well as track, $F(1, 158)$ = 0.00, P = 0.962, were both non-significant as well.

Similarly, a two-way ANOVA predicting growth mindsets of change perceptiveness yielded an identical pattern of results. The higher-order interaction between mobility and track was non-significant, $F(1, 158) = 0.49$, $P = 0.485$. In addition, neither the main effect of mobility, $F(1, 158) = 0.03$, $P = 0.857$, or track, $F(1, 158) = 1.20$, $P = 0.274$, was statistically significant as well.

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