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Fictional Role Models and Early Interest in STEM

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We test whether exposure to fictional role models can impact interest in STEM at young ages. We run an in-curricula field experiment in which children aged between 10 and 12 are randomly assigned to work on an 8-week long project on the biography of a STEM professional. We find that the intervention increases their willingness to pursue a career in a STEM field when they grow up, particularly in Engineering. The effect operates on the extensive margin, attracting those with no previous interest in STEM. Our results show that the use of fictional role models can be effective, making them a low-cost and easily scalable policy.

JEL-Classification: D91, I21, I28, J24.
Keywords: role models, college major choice, STEM

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1. Introduction

STEM skills are central to innovation and economic growth (Bianchi and Giorcelli, 2019; Peri et al., 2015), and STEM degrees are among those with the highest earnings returns (Altonji et al., 2012, 2014; Arcidiacono, 2004; Kirkeboen et al., 2016). Yet relatively few students pursue STEM fields (Card and Payne, 2021; Delaney and Devereux, 2019). Attrition occurs at multiple stages of the educational pipeline, long before students make formal specialization choices (Bettinger, 2010; Brainard and Carlin, 1998; Seymour and Hewitt, 1997; Speer, 2023; Stinebrickner and Stinebrickner, 2013). Because educational paths are highly path-dependent, early beliefs about ability, effort, and interest strongly influence later choices. This makes late interventions costly and potentially less effective, and points to the importance of shaping academic interests at younger ages, before prior choices restrict future educational trajectories. One promising approach is the use of role model interventions, which have been shown to successfully steer interest in STEM (see e.g., Breda et al., 2023; Porter and Serra, 2020). However, its costs (e.g., role model recruiting, coordination, and travel) can limit their use in many contexts. Fiction is a cheaper alternative, and exposure to role models through television and movies has already been shown to affect real-life decisions on fertility, divorce, and schooling (Chong and La Ferrara, 2009; La Ferrara et al., 2012; Jensen and Oster, 2009; Riley, 2024).

In this paper, we take fiction into the classroom and test whether fictional role models steer interest in STEM at young ages. We conduct an in-curricula experiment in 53 schools in Uruguay with 5th and 6th grade students (aged 10 to 12), approximately four years before their first formal high school choice. Students make a choice of high school track after 10th grade, with only the *Engineering* endline track leading directly to STEM degrees. Our intervention is implemented as an 8-week project. Students participate in weekly 45-minute sessions that include classroom discussions and the preparation of a coded animation, guided by the classroom teacher and a remote teaching assistant. We randomly assign schools to one of the two versions of the project. In the Biography version (treatment), students work on the life story of a fictional STEM professional. In the Emotion version (control), students work on different emotions. Both versions share the same instructional format, duration, and coding activities, and differ only in their topic. All students are therefore exposed to programming, but only treated students are exposed to a STEM role model.

We find that working on the biography of a STEM professional raises early interest in Engineering by 7.0 percentage points, a 31 percent increase relative to the control group. The effect is specific to Engineering, the main STEM pathway in the Uruguayan context, and interest in other fields remains unchanged. In an average class of 24 students, the intervention adds between one and two students interested in Engineering to the five or six who already are. We find that the intervention is effective for students whose previous year GPA is below the median: Their increase in interest in STEM is twice that of the average effect. We also show that the intervention operates on the extensive margin. We categorize students based on open-text reports on career interests before the intervention, and identify everyone that declared at least interest in one STEM field. The increase is concentrated on those who have not declared STEM interest beforehand. These are the students that would not consider STEM otherwise, and attracting them could matter. The gains from graduating in STEM hold in Uruguay (Amarante et al., 2025), and evidence from the region shows that they reach less-prepared students (Ng and Riehl, 2024).

We further study which features of a role model matter by introducing variations within our intervention. We implement a 2x2 design that varies the gender of the character (male or female) and the presence of a growth mindset narrative. Growth mindset biographies highlight early academic struggles and the effort required to succeed, and the other biographies portray a relatively effortless path to achievement. Apart from these two features, the stories are identical. Our findings indicate that all four biographies increased interest in engineering, although some estimates are imprecise. Point estimates are larger for biographies with a growth mindset narrative and for biographies with a male character. In line with previous studies, we find evidence of gender homophily, which is entirely driven by boys. We also explore the mechanisms behind the increase in interest in Engineering. Focusing on the whole sample, we find no changes in field understanding, perceived self-competence, course preferences, or beliefs about effort and gender, and none of them mediates the total effect. Among students with no previous interest in STEM, the biography raises perceived self-competence in Engineering and preferences for mathematics, and these two account for a third of the effect. Among students with low GPA, none of these variables accounts for the effect.

Our results show that role models need not be real to be effective. A fictional role model, delivered within regular class time, raises interest in Engineering among the students least likely to consider it. We thus show that fictional role models are effective interventions which are simple to replicate and scale.

Related literature. Our work relates to the growing literature on degree and college major choice (e.g., see Altonji et al., 2012, 2016; Patnaik et al., 2021, for reviews). These studies have almost exclusively examined choices made just before college entry or during college. Breda et al. (2023) comes closer to our study, as it examines high school track choices prior to college and center in pathways toward STEM fields. Other studies examine track choices at ages closer to those of our sample, before 9th grade (Giustinelli, 2016) and before 7th grade (De Groote and Declercq, 2021; De Groote, 2025). However, these tracks differ in their pathway to university and not in their field, and these studies align more closely with the literature on educational choice (i.e., university enrollment). Our focus is on students' degree interests several years before the actual choice, which, given the inflexibility of educational pathways, conditions which college degrees are chosen. We find that role model interventions, even toward the end of primary school, can have a substantial impact on interest in college degrees.

We also contribute to the literature on role model interventions in education (see Gomez-Ruiz, 2025, for a review). Many studies have shown that both long-term (Bettinger and Long, 2005; Bleemer, 2016; Carrell et al., 2010; Gershenson et al., 2022; Lim and Meer, 2017, 2020) and short-term (Breda et al., 2023; Patnaik et al., 2024; Porter and Serra, 2020; Riley, 2024) exposure to role models effectively alters educational choices and outcomes. We extend these results to mid-duration interventions embedded within the course of study using fiction.[1] The use of fiction has been previously explored in non-educational contexts (see e.g., Chong

[1] Related work in psychology has examined how biographical narratives of role models shape students' STEM interest, attitudes, and performance. For instance, Shin et al. (2016) show that exposing undergraduate students to biographies highlighting struggle and effort instead of innate ability increases STEM interest, sense of belonging, and identity matching. Similarly, Bagès and Martinot (2011) show with fifth graders students that while the gender of a hardworking role model does not affect math test performance, children perform better with a female than a male role model when success is attributed to innate ability. However, our study differs from this psychology literature across several dimensions. First, while Shin et al. (2016) focus on US undergraduates who have already entered higher education, we examine early occupational interest among students in primary education before any critical educational decisions are made. Second, although Bagès and Martinot (2011) study a similar age

and La Ferrara, 2009; La Ferrara et al., 2012; Jensen and Oster, 2009; La Ferrara et al., 2012). Our paper is closest to Bernard et al. (2023) and Riley (2024), who focus on educational outcomes and deliver role models through documentaries and movies. We differ from both in the outcome, as they measure school enrollment and exam performance, and we measure students' interest in professional fields. Bernard et al. (2023) also treat adults, and we treat the students themselves. Riley (2024) studies a single movie screening, and we study an 8-week project embedded in the curriculum.

Organization. The remainder of the paper is structured as follows. Section 2 provides institutional background of the Uruguayan educational system and its pathway to STEM studies. Section 3 explains the experiment design and its implementation. Section 4 describes the data collected. Section 5 shows our main findings. Section 6 concludes.

2. Institutional Context

2.1. College Degree Choice

In Uruguay, students enroll directly in a university degree, and the use of majors or minors is negligible as of the time of our intervention. Each degree has its own coursework, and students must complete it to graduate. Changing degrees is costly: a student who switches has to start over the coursework of the new degree. This path dependence traces back to high school, as the degrees a student can enroll in depend on the tracks chosen there. All students complete the same coursework up to 10th grade. In 11th grade, students choose one primary track that constrains future educational choices. The tracks are *Art*, *Biology*, *Humanities*, and *Scientific*. In 12th grade, students choose an endline track conditioned on their 11th-grade track.[2]

The high school system has high switching costs. A student pursuing an endline track not directly linked to their primary track must complete the coursework for the preceding track first. Upon completion of high school, all students have the right to access university. Endline tracks determine which university degrees a student can enroll into. Each degree requires specific endline track completion. In some cases, students from different and pre-specified endline tracks can be admitted, conditioned on the approval of additional high-school level exams. For STEM degrees, the *Engineering* endline track is the primary pathway for enrollment.

The share of students in STEM-oriented studies is persistently low (see Figure B.1). Within high school, 14% of 11th grade students take the *Scientific* track, while almost 80% go either into *Biology* or *Humanities*.

group, their intervention was a one-off exposure immediately before a math exam, whereas we implement a medium-term intervention under regular classroom conditions.

[2] The system originated in the 19th century, integrated to the country's sole university. The university was in charge of the final years of high school. 11th and 12th grade where grouped into different tracks conceived as preparatory programs for university admission. The curriculum was highly specialized, since each track was designed to satisfy the entrance requirements of specific faculties. By the 20th century, high school governance became independent from the university, but maintained the same preparatory logic. The first formal high school plan was approved in 1941. High school was organized around 3 primary tracks (*Biology*, *Humanities*, and *Scientific*) and 6 linked endline tracks (*Medicine*, *Agronomy*, *Law*, *Business*, *Architecture*, and *Engineering*). Successive reforms in 1963, 1976, and 1993 kept the primary and endline tracks unchanged. In 2006 an *Art* track was added, connected to a single endline track also labeled *Art*.

Toward 12th grade, 9% of enrolled students are in *Engineering*, a similar share to *Art* and to *Business*, above the modest shares in *Agronomy* and in *Architecture*, but far below the most popular *Medicine* and *Law* (with around 35% of the students, each).

2.2. High School Projects

Our intervention is embedded within a high school program on computational thinking (CT). The program focuses on developing critical thinking, creativity, and problem-solving skills (Wing, 2017). Training in such skills has been rapidly expanding into formal K-12 education settings around the world. For example, most European countries had included CT skills as part of mandatory education curricula in the early 2020s (Bocconi et al., 2016, 2022; Bers et al., 2022).

The CT program is open to public school teachers of 4th to 6th grade. Teachers voluntary enroll to the program and are randomly linked with a trained remote instructor. The remote instructor leads weekly classes, while the teacher is present in the classroom. The program is based on projects covering various topics that complement general education (e.g., history, geography, natural sciences, and mathematics). Students in an enrolled teacher's class follow the program as mandatory, and they all follow the same projects simultaneously. The first project is used to introduce the use of Scratch, a programming language designed for children that uses visual elements resembling building blocks to create animations.[3] Instructors receive a project guide prior to its implementation. The project is centered on either biographies or emotions. Biography projects present students a life story. Students revisit the same biography each session and prepare an animated representation of it. Emotion projects encourage students to explore and express emotions. Students discuss a different emotion each session and prepare animated representations of it. Appendix E covers in detail the guidelines for each type of project.

3. Experiment design

The experiment is designed to investigate the impact of role models on students' academic perceptions and aspirations. The analysis plan was preregistered with the AEA RCT Registry (AEARCTR-0013425). Deviations from the preregistration are noted and explicitly explained in Appendix D.

3.1. Experimental arms

We randomly assign all classes in a school to work on a biography or on emotions in the first project of the CT program.[4]

[3] Scratch is a programming language used as an educational tools for children. The language is visual, based on graphical elements resembling building blocks. Scratch is developed by the MIT Media Lab and is widely used worldwide, having been translated into more than 70 languages and used in over a billion projects. For more information about Scratch, visit https://scratch.mit.edu/about.

[4] We do so by delivering different project guidelines to the instructors. Instructors only receive their treatment arm teaching guide. Instructors who teach in more than one class, are alwasy assigned to the same treatment arm. After the data recollection process ended, teachers and instructors were debriefed about the content of the project guides of all treatment arms. The Biography project guides were designed in collaboration with Ceibal, a public agency that promotes technology inclusion into education and organizes the program. The process involved extensive back and forward discussions. Final inclusion of content into the project required mutual agreement between the agency and the research team. The Emotions project guide was designed

The control group is the Emotions project (T0). Students feature themselves as the main character, reflect on the emotions they feel and the situations that trigger them, and create a story with two emotions of their choice (e.g., joy, fear, or anger). The project does not feature any professional figure or content. A drawback of this control group is that it is an intervention in itself, and working on emotions may steer students toward other fields (e.g., social work, or art). If that were the case, interest in those fields would be higher in the control group, and we find no evidence for it (see Figure 3).

The Biography project is our treatment group (T1-T4). We restrict the biographies to focus exclusively on a fictional STEM professional's life and achievements. The main character is described from an early age up to a successful career in computer engineering. We introduce four manipulations to the Biography projects in a 2x2 between-subject design with randomization at the class level. Treatment arms T1-T4 differ on the gender of the biography (either male or female) and the presence or absence of growth mindset (see Table 1). Female biographies depict the life story of Maria and male biographies depict the life story of Juan, the two most common names in Uruguay.[5] Biographies without growth mindset present a rather effortless professional, portraying challenges as enjoyable adventures easily navigated thanks to natural talent and curiosity. In contrast, biographies with growth mindset detail the professional's academic struggles, emphasizing the challenges faced during formative years and the effort, perseverance and diligence that allowed overcoming obstacles and attaining success.

3.2. Data collection

We collect data in two waves: baseline and endline. The baseline wave is focused on socio-demographic information. The endline wave includes all outcome variables. We collect data for students and educators (i.e., teachers and remote instructors). Our main focus is on students.

Prior Interest in STEM: We include an open-ended question in the baseline survey: *What would you like to do when you grow up?*. We coded these responses into STEM and non-STEM fields. We categorize students as previously interested in STEM if their response contains any STEM field, and not interested otherwise.

Professional Fields: We use a set of questions to assess participant's interest, understanding and perceived self-competence (Grosch et al., 2022) in different professional fields. For a set of fields, participants indicate their level of interest, understanding, and belief in self-competence. We focus on six fields: engineering, computer science and programming, mathematics, social work, language and culture, and art and design. We classify the first three as STEM and the other as non-STEM (following National Science Foundation, 2021).

Course Preferences: We capture numerical and verbal preferences using a set of 8 questions for each task type.[6] We apply Principal Component Analysis (PCA) and use the first principal component as a measure

by Ceibal. The focus is on exploring and expressing children emotions.

[5] Maria is the most common name in Uruguay since records began in 1902, and Juan is the most common male name (Instituto Nacional de Estadística, 2025). Neither name is tied to a particular generation. Maria and Juan were also the most common names among babies born the year before our intervention.

[6] This approach enables us to assess both math and verbal preferences. It is also useful for our main outcomes, as it mitigates the potential experimenter demand effect on children that perceive the experiment as solely numerical-related.

of preference for task type. We also compute a binary variable for favorable agreement on each item, and construct indicators based on them.[7]

Beliefs on Growth Mindset: We use a set of questions on beliefs on fixed or growth mindset (Bettinger et al., 2018). We ask participants about their beliefs of intelligence as being fixed, perceptions of capacity to improve own maths skills, and whether effort exertion signals lack of ability. Questions are asked both focusing on oneself and on each gender (e.g., *'Do you believe you/girls/boys can change your/their level of intelligence?'*).

Beliefs on Gender Stereotypes: We focus on three types of stereotypical thinking: explicit, implicit, and social. To assess explicit stereotypes, we ask separately about numerical and verbal task performance among boys and girls. We survey ability on task, effort needed to achieve a minimum passing grade, and future usefulness. To assess implicit stereotypes, we use a children-adapted Implicit Association Test (IAT) (Cvencek et al., 2011; Greenwald et al., 1998; Grosch et al., 2022) covering gender and numerical/verbal tasks. To assess social stereotypes, we use the same items of the explicit measure but focusing on peer's perceptions.

3.3. Procedures

The academic year in Uruguay runs from March to December. Treatment randomization was run in April and the intervention started in May. Baseline data for educators was collected in April, before randomization. Baseline data for students was collected in May, after randomization. Endline data for both educators and students was collected in September.

The experimental procedure is illustrated in Figure 1. In January, teacher enrollment opened. Enrolled teachers are linked to a remote instructor. In March, we invited enrolled teachers to participate in the intervention. Participation was voluntary. Interested teachers needed to complete a short form and were invited to a webinar that explained the project, including its workload implications, main objectives, and schedule. In April, the randomization was run at the school level. We used socio-economic context for stratification.[8] Within each stratum, schools were randomly assigned to one of the five treatment arms.

4. Data

In total, 73 teachers completed the baseline survey in April. Among them, 8 dropped out before the intervention began, and 4 during the intervention. This resulted in 1,453 children participating in our intervention, which was conducted across 61 classes.

[7] The 8 items asses whether courses are (1) enjoyed, (2) found interesting, (3) loved during classes, (4) loved as homework, (5) considered enthusiastic, (6) favorite, (7) boring, or (8) avoided for studying. We reverse the negative assessments (items 7 and 8) to compute the favorable agreement. Each item is answered through a 5-point Likert scale. We consider agreement and strong agreement as 1, and 0 otherwise.

[8] School's socio-economic context is determined by household characteristics in the catchment area. The variable is constructed by the government, based on parent's educational attainment, household material and location conditions, and social transfer reception. We construct a binary indicator using the socio-economic variable, distinguishing schools in poor and non-poor neighborhoods.

We exclude two classes from the analysis. One class is excluded because they did not engage in the projects, as no remote instructor was assigned. The other class was excluded because the teacher did not complete any surveys or monitoring activities. As a result, the final sample includes 1,401 students across 59 classes in 53 different schools. We further excluded students who did not provide responses in both the baseline and endline surveys, resulting in a final sample of 1,017 students, representing 73% of the original sample (see Figure 2).[9]

Tables C.1 and C.2 present a balance check for students and teachers respectively.[10] Student baseline characteristics (e.g., gender, age, presence of both parents at home, number of siblings, caregiver skills, and use of technology) are well-balanced, with small and statistically insignificant differences. Educators baseline characteristics (e.g., age, education, experience, task preferences) are also similar across control and treatment groups, except for age and math preferences. Given these differences, we include controls for instructor's age and math preferences in our analysis to account for potential baseline differences.

5. Results

In this section, we present the main results. First, we describe interest in all professional fields and distinguish by student's characteristics. Second, we show the treatment effects on early interest in STEM, course preferences, and beliefs about competence for pursuing STEM. Third, we present heterogeneous effects by students' gender, socio-economic context, ability, and initial interest in STEM. Last, we explore the mechanisms that may explain our results.

5.1. Early Interest in Professional Fields

We first explore student's interest in STEM. We begin by focusing on interest in the baseline survey. This variable covers all STEM fields (e.g., engineering, computer science, natural sciences, health, and economics). On average, 30% of participants report a STEM field in the open-text response. Table B.1 reports the share of students across several student characteristics. Girls, high-GPA students, and students from

[9] We include 39 children who faced difficulties with the Implicit Association Test but answered all other questions. For robustness, we also estimate the model using the sample of children with complete responses for both periods of time, totalizing 1,003 students. In the baseline survey, 33% of students left blank the question regarding their parents' education, and 3.2% left blank the question regarding their parents' occupation. However, to include all observations we adopt a method outlined in Zhao and Ding (2022) known as the *missingness-indicator method (mim)*. This technique involves incorporating a missingness indicator into the main regression model as an additional full baseline covariate. The indicator is introduced mean-centered and interacted with the treatment variable.

[10] The tables display ordinary least squares estimates of the treatment dummy on the variables listed in the first column, with standard errors clustered by school. For simplicity, we compare the control group (`T0`) to the four treatment groups combined (`T1-T4`). Table C.1 compares student baseline characteristics between the control group (N=225) and the treatment group (N=792). The results indicate that the two groups are generally well-balanced across most variables, with small and statistically insignificant differences. Table C.2 compares baseline characteristics of teachers and remote instructors between the control group (N=12) and the treatment group (N=47). The results show that, on average, treated teachers are slightly older than those in the control group, with a difference of 3.5 years. Similarly, treated remote instructors are older, with a difference of 6.3 years that was significant at 90% of confidence level. Preferences across subjects, including math, verbal, science, social science, and computational thinking, are comparable, except for math, where treated teachers report higher preference scores significant at 90% of confidence level. Given these significant differences, we include controls for teacher and remote instructor age, as well as teacher math preference, in our analysis to account for potential baseline differences.

schools in non-disadvantaged neighborhoods show higher initial interest in STEM. The inclusion of a broader set of fields (particularly health) explains the high share among girls.

We then focus on the structured endline responses among students who participated in the emotions project (T0, N=225). Most students show interest in at least one professional field (87%). More than half are interested in two or more fields (62%), and less than 5% express interest in all fields. The most popular field is Art, with 59% of students interested. Coding is the second most popular, with 41% of students interested. The least popular field is Engineering, with only 23% of students interested. 63% of students report interest in at least one STEM field, and 8% report interest in all of them.

Figure B.2 further explores field interest across subgroups. Field interest is different by gender. Girls are less interested in STEM fields, particularly in Engineering and Coding. In turn, they are much more interested in Art. Interest also differs by student's GPA. Students with a lower GPA are less interested in Engineering and Art. There are no significant differences in field interest by school socio-economic context. Students initially interested in STEM show higher interest in Engineering and Coding, and lower interest in Art.

5.2. Treatment Effects

Table 2 reports the main results from our intervention. We assess the impact of the exposure to STEM biographies on early interest in STEM fields. We compare students working on an 8-week project on biographies (T1-T4) with those working on a project on emotions (T0). This tests whether exposure to any STEM role model increases interest in STEM.

We find a positive effect for interest in all three STEM fields combined, with an effect magnitude of 3.9 percentage points (SE=.019 and p-value=.049, see column 1). The increase is driven by interest in Engineering, which increases 7.0 p.p. (SE=.032 and p-value=.033, see column 3) and stands 31% above the mean in the control group. Figure 3 shows interest in each field. The increase in interest in Engineering does not come at the expense of other fields, as we find no significant change in interest in Computer Science (p-value=.984, see column 4), in Mathematics (p-value=.796, see column 5), nor in non-STEM fields (i.e., Social Work, Culture, and Art). Two features of our setting may explain why the effect appears only in Engineering. Engineering is the least popular field in the control group (23%, against 34% for Mathematics and 41% for Coding), and it has the most room to grow. Students in the control group also program in Scratch and study Mathematics at school, and the biography adds little exposure to these two fields.

The size of the effect is economically meaningful. The average class in our sample has 24 students, and between five and six of them state interest in Engineering in the control group. Our intervention adds one or two students per class. This is large relative to actual enrollment, as only 9% of 12th grade students are in the *Engineering* track, or about two students in a class of 24. If the additional interest translated into enrollment at the same rate as existing interest, the share of students in the *Engineering* track would rise from 9% to about 12%.[11]

[11] This calculation assumes that the ratio between enrollment in the *Engineering* track and stated interest in Engineering in the control group holds for the students whose interest changes with the intervention. The enrollment share is computed among students currently enrolled in 12th grade, and not among the students in our sample.

We also examine whether our intervention changes how students perceive their self-competence for pursuing a STEM field and mathematics courses in high school. Table A.5 shows the treatment effects on self-competence for pursuing each STEM field. Though point estimates are positive, we find no significant changes in the beliefs students have on whether they will be good in any STEM field (p-value=.407 for Engineering, p-value=.380 for Computer Science, and p-value=.211 for Mathematics). We also do not find changes in students' preferences for mathematics courses (see Table A.8).

Heterogeneities. Table 3 shows treatment effects in interest in Engineering for different population subgroups. First, we explore whether the results are present for both genders. In other words, if boys or girls are more likely to change their interest in STEM once exposed to the biographies. We find positive point estimates in Engineering for girls (β=.037, SE=.037, p-value=.332 and equivalent to a 20% increase, see column 2) and boys (β=.093, SE=.049, p-value=.062 and equivalent to a 32% increase, see column 3), but with reduced statistical significance possibly due to reduced power.

Second, we compare treatment effects by socio-economic context of the school. We find similar increases in interest in Engineering among students from disadvantaged (β=.060, SE=.047 and p-value=.214, see column 4) and non-disadvantaged background (β=.072, SE=.040 and p-value=.081, see column 5).

Third, we assess treatment effects by students' GPA. We find a 16.3 p.p. increase in interest in Engineering among low GPA students (SE=.061 and p-value=.010, see column 6), doubling the interest of the control group. In contrast, our intervention yields a null impact on high GPA students (β=-.002, SE=.047 and p-value=.959, see column 7). Treatment effects differ between both groups at 10% confidence interval (p-value=.051, see column 7).

Fourth, we explore treatment effects by region. We find that students from outside the capital city increase their interest in Engineering by 8.3 p.p. (SE=.037 and p-value=.031, see column 9). However, treatment does not change the interest in Engineering among students in the capital city. Treatment effects differ between these two groups (p-value=.008, see column 9).

Finally, we examine treatment effects by initial STEM interest. We find that treatment effects are entirely driven by the extensive margin. Interest in Engineering rises by 10.9 p.p. (SE=.036 and p-value=.003, see column 10) among students who declared no interest in STEM before the intervention, In contrast, we find no change for those who declared interest in STEM beforehand (β=-.014, SE=.053 and p-value=.793, see column 11). Treatment effects significantly differ between both subgroups (p-value=.034, see column 11).

Biography Content. We then explore whether the content of the biography makes a difference. That is, if certain characteristics of the role model are relevant. Our manipulation alters two features of the biographies: growth mindset and the gender of the character. Table 5 shows how these differences impact interest in Engineering.

Biographies with growth mindset highlight the path from struggling with learning to becoming an expert. These biographies enhance interest in Engineering by 10.8 p.p. (SE=.035 and p-value=.004, see column 2), representing a 47% increase. Biographies that do not include growth mindset ideas yield lower and

nonsignificant point estimates (β=.055, SE=.037 and p-value=.153, see column 3). However, we lack statistical power to establish a significant difference between both type of biographies even at the 10% confidence interval (p-value=.202, see column 3). Table A.2 further explores overall interest in STEM distinguishing between biographies by growth mindset inclusion. The point estimates of the treatment effects are larger for biographies including growth mindset. We again find that interest in Engineering drives a positive effect on all STEM fields combined, while coding and mathematics remain unchanged. To test whether this biography dimension has a differential impact we compare classes working with biographies with and without growth mindset. We find no significant differences across any of the main outcomes (see Panel C).

Biographies also differ in the gender featured. Male biographies yield a 10.8 p.p. increase in interest for Engineering (SE=.030 and p-value=.001, see column 4), while female biographies have a positive but nonsignificant impact (β=.065, SE=.043 and p-value=.140, see column 5). Again, we cannot determine that the difference between both types of biographies is statistically significant at the 10% confidence interval (p-value=.318, see column 5). Table A.3 shows the impact for all STEM fields. Comparing female biographies with male biographies, we find no differential impact (see Panel C of Table A.3).

5.3. Mechanisms Exploration

We next explore plausible mechanisms that can account for the higher interest in Engineering that our intervention triggers. First, we examine the importance of identity match between students and role models. Second, we assess whether understanding of the field and confidence in own performance mediate the result. Third, we explore whether preferences for courses included in the field syllabus change. Fourth, we analyze if beliefs about gender differences and the relevance of effort in academic success are affected. Last, we focus on the subgroups that drive the treatment effect: students with a low GPA and those who were not previously interested in STEM.

Identity Match. We examine whether identification with the role model is relevant for the treatment effect. Our setting allows us to explore identity in two dimensions: gender and ability.

Table 6 shows our results. First, we compare students whose gender is the same as the role model (i.e., boys in treatment arms T1 and T2, and girls in treatment arms T3 and T4), with those with unmatched gender identity (i.e., boys in treatment arms T3 and T4, and girls in treatment arms T1 and T2). Students who have their gender identity matched increase their interest in Engineering by 9.7 p.p. (SE=.037 and p-value=.011, see column 1), while those with unmatched gender identity show a non-significant rise of 6.3 p.p. (SE=.040 and p-value=.122, see column 2). The results are in line with previous previous studies that show that gender match makes role model interventions more effective (see e.g., Breda et al., 2023; Porter and Serra, 2020). However, in our experiment the effect is mostly driven by boys (see Table A.1).

Then, we focus on ability by leveraging student's GPA. We consider that low GPA students have their identity matched when they work in a project that portrays growth mindset (i.e., biographies that detail academic struggles, such as treatment arms T2 and T4), and that high GPA students match when working with biographies without growth mindset (i.e., biographies in which academic challenges are easily navigated,

such as treatment arms T1 and T3). Though we find positive point estimates when ability is both match and unmatched, only students assigned to biographies with unmatched ability significantly increase their interest (β=.119, SE=.026 and p-value<.001, see column 4). This result contradicts our pre-registered expectations, which prompts us to consider other explanations. On the one hand, it casts doubt on our assumption that measured ability is the relevant dimension for the match. We expected biographies with a growth mindset to be more helpful for students who believe they lack the ability to succeed in a profession. We proxy this perception with students' GPA, but we have no measure of students' perceptions of their own abilities before the intervention and therefore cannot verify this assumption. On the other hand, the result may reflect an inherent trade-off in growth mindset narratives. While these stories aim to show that academic struggles can be overcome through effort, they may end up emphasizing the high effort costs of pursuing a profession and reduce willingness to engage (particularly for low-GPA students). In contrast, biographies in which academic obstacles are not salient may act as a stronger aspirational signal, as they focus on success rather than on the effort required to achieve it.

Field Understanding and Self-Competence. We test whether the treatment effect is mediated by field understanding and perceived self-competence in the field. We first show that both are positively correlated with interest in the Engineering field. Those interested in the Engineering fields are 25.5 p.p. more likely to understand the field and 37.2 p.p. more likely to perceive to have self-competence for it (see Table A.4). We also test whether each variable changed due to the intervention. We find null results for both, even when only considering the biographies that portray growth mindset (see Table A.5). Table 7 shows the formal mediation analysis and confirms that neither variable serves as a mechanism driving the treatment effect on Engineering interest (see Table A.6 for a more detailed analysis).

Course Preferences. We analyse whether course preferences change due to the intervention. We focus on numerical and verbal tasks. We find that those who are interested in Engineering like more numerical tasks, while are not different in their interest for verbal tasks (see Table A.7). However, the preferences for courses are not impacted by the intervention (see Table A.8). As expected, Table 7 shows that course preferences are not a primary drivers of our main results (see Table A.9 for a more detailed analysis).

Beliefs. We focus on beliefs related to growth mindset (i.e., whether intelligence can be changed, math skills can change, and whether exerting effort is good) and gender stereotypes (i.e., explicit first-order and second-order gender stereotypes, and implicit gender stereotypes). We find that none of these variables are positively correlated with interest in Engineering (see Table A.10), nor positively impacted by our intervention (see Table A.11). Table 7 confirms that beliefs are not mediating the observed increase in interest in Engineering (see Table A.12 for a more detailed analysis).

Focus on Most Impacted Subgroups. In order to get a better understanding of how the intervention works, we explore the subgroups that drive our main results: students with low GPA and with no previous interest in STEM.

Panel B in Table 7 focuses on students whose GPA in the previous year was below the median, for whom

exposure to a STEM biography rises interest in Engineer by 16.3 percentage points. We examine whether the previously explored variables serve as the underlying channels through which we observe a positive effect on interest in Engineering. Accounting for all plausible mediators leaves the main treatment effect rather unchanged (p-value=.634 for the difference between coefficients, see column 5).

Panel C in Table 7 focuses on students who did not declare to be interested in any STEM prior to the CT program. Exposure to the biography project raised Engineering interest by 10.9 percentage points in this subgroup. We find that beliefs about self-competence for the field and course preferences partially account for this treatment effect. The main treatment effect is reduced by 20% once we account for perceived self-competence (p-value=.058 for the difference between coefficients, see column 2). Similarly, controlling for course preferences reduces the main treatment effect by 20% (p-value=.021 for the difference between coefficients, see column 3). When we account for the full set of plausible mediators, the main treatment effect is reduced by 33% (p-value=.005 for the difference between coefficients, see column 5).[12]

We further explore how the intervention impacts each mediator in the latter subgroup. Table A.13b shows a positive treatment effect on self-competence for Engineering, the effect being larger for biographies that feature growth mindset. Similarly, Table A.14b shows a positive treatment effect on math perception, the effect being large and significant for both biographies. Interestingly, effort and gender beliefs also change as a result of the intervention, but do not mediate the effect on interest in Engineer (see Table A.15b). Exposure to STEM biographies reduces the belief that mathematics ability is fixed by 10.8 percentage points for students with no prior interest in STEM (see column 2). This drop is even larger when students are exposed to growth mindset biographies (see column 7).

Finally, we focus on the content of the biographies to analyze whether this specific component is responsible for the observed effect. Table A.16 shows that growth mindset treatments yield a significant increase in Engineering interest among students with no prior STEM interest. In turn, among low-GPA students (see Table A.17), treatments without growth mindset also show a large and significant effect. Nevertheless, similar to the subgroup with no previous interest in STEM, there are no statistically significant differences between the two treatment arms. Again, both gender biographies increase interest in Engineering, although the difference between male and female treatments is not statistically significant for either subgroup: those with no baseline interest in STEM and those with low GPA (see Tables A.18 and A.19).

6. Conclusion

There is an undersupply of students with STEM skills. Role models can steer students toward these fields, but bringing a professional into a classroom requires recruiting, coordination, and travel, and more so for schools far from where these professionals work. We test whether the use of fictional role models can also raise interest in STEM. The intervention is effective. An 8-week project on a STEM professional biography raises interest in Engineering by 31%. In a class of 24 students, this adds one or two students interested in Engineering to the five or six who already are, with no drop in interest in other fields. We reach students

[12] Similar results are found when restricting the analysis to growth mindset treatments (see Table **??**). A detailed analysis can be found in the Online Appendix.

before they choose their high school track, and no previous choice restricts which degrees they can enter. Following these students into high school would show whether it eventually becomes enrollment.

The effect is larger for students who start further away from STEM. Interest in Engineering doubles among students with low GPA and rises among students with no previous interest in STEM, and we do not detect a change among students with high GPA or with previous interest. Among students with no previous interest in STEM, the biography raises perceived self-competence in Engineering and mathematics course preferences, which account for a third of the effect.

Our design is a novel role model intervention. It is of mid duration, it is embedded in the curriculum, and it combines exposure to a professional with the use of fiction. Its implementation is low-cost, as the biography is a topic of a project that classes already do, and its only additional input is the project guide. These features make the intervention easy to implement in remote places and highly scalable. A fictional role model does not need to reach the school: it arrives within the curriculum.

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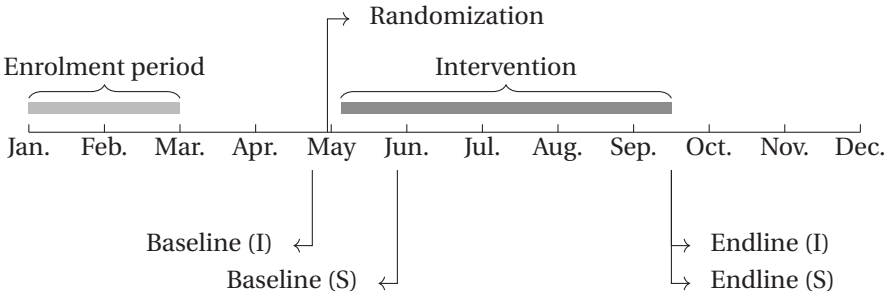
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Tables and Figures

Table 1: Treatments

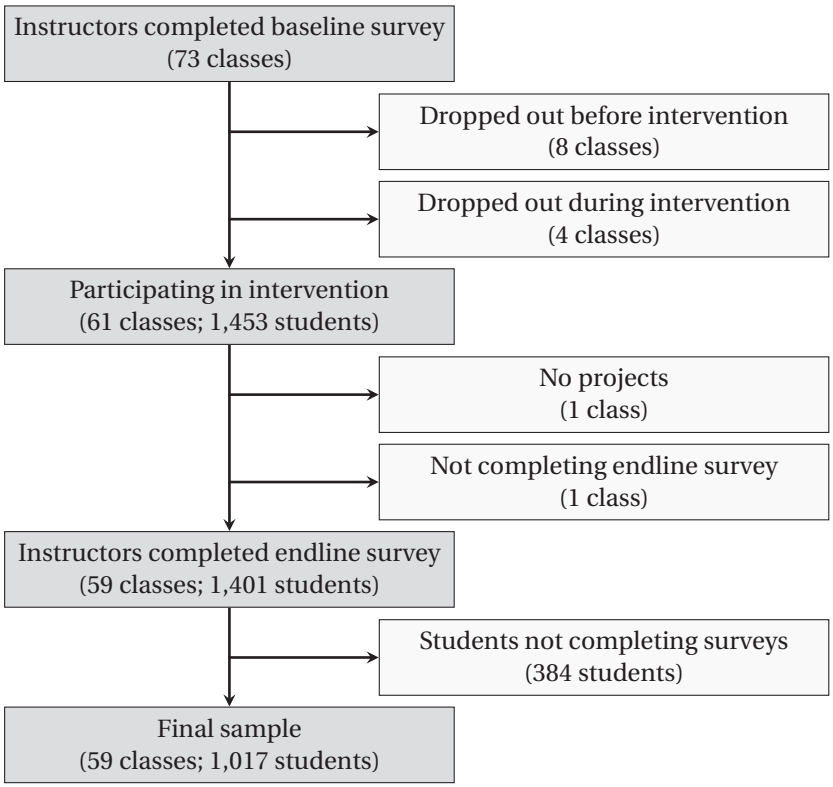
Treatment	Project (1)	Gender (2)	Growth Mindset (3)
T0	Emotions	-	-
T1	Biography	Male	✖
T2	Biography	Male	✔
T3	Biography	Female	✖
T4	Biography	Female	✔

Notes: This table shows the differences across treatments arms. Column 1 shows the type of project: Biography or Emotions. Columns 2 and 3 focus on the key features of the story in the Biography projects. Column 2 indicates the biography gender. Column 3 indicates the presence or absence of a growth mindset narrative. Growth mindset is present when the biography emphasizes the academic struggles faced in childhood, and absent when those struggles are not mentioned.



Notes: This figure summarizes the experimental procedures. Teacher enrollment started in January, with a deadline in March. Teacher baseline characteristics were surveyed from April 22 to April 30. Randomization was conducted on April 30. The intervention ran from May 6 to September 16. Most classes started on May 6 and finished on July 22. Some classes had later starting and finishing dates. Student baseline characteristics were surveyed from May 27 to June 2. endline surveys were collected from September 6 to September 27.

Figure 1: Experimental procedures



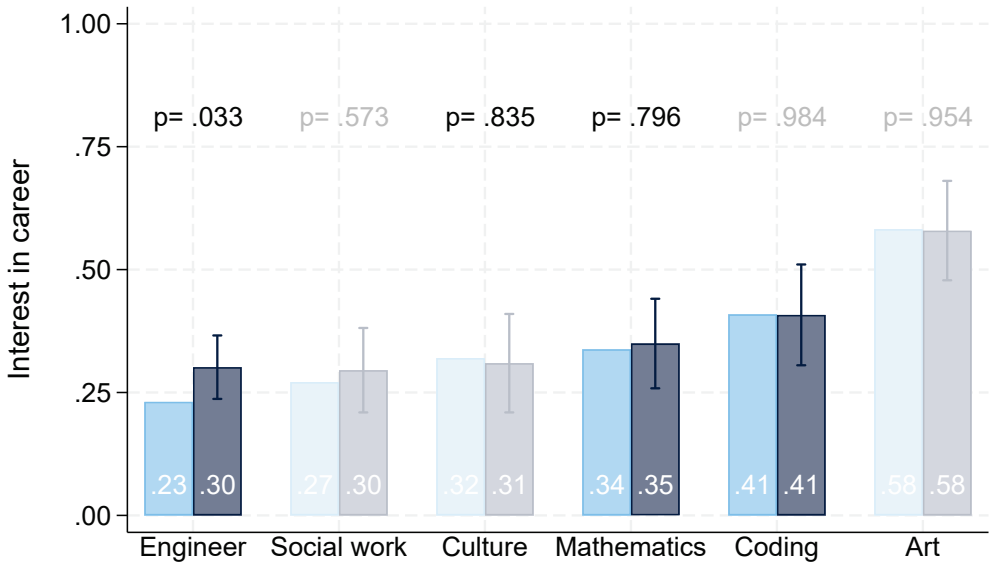
Notes: This figure summarizes the sample exclusions applied in the analysis. Sample sizes are reported for exclusions and after exclusions.

Figure 2: Sample exclusion

Table 2: Treatment Effects on Early Interest in STEM and Self-Competence

	STEM		Career		
	All	Any	Eng.	Coding	Maths
	(1)	(2)	(3)	(4)	(5)
Panel A. Career Interest					
Biography	.039**	.006	.070**	-.001	.012
	(.019)	(.038)	(.032)	(.051)	(.045)
Dep. var. mean	.08	.63	.23	.41	.34
Effect magn.	49%	1%	31%	0%	3%
Observations	1,017	1,017	1,017	1,017	1,017
R^2	.013	.009	.006	.016	.013
Panel B. Self-Competence					
Biography			.025	.029	.045
			(.030)	(.033)	(.036)
Dep. var. mean			.2	.32	.31
Effect magn.			13%	9%	15%
Observations			1,017	1,017	1,017
R^2			.005	.014	.006

Notes: This table reports the coefficients of the treatment dummy on variables capturing career interest (Panel A) and self-competence (Panel B) in STEM fields. The independent variables are computed as dummy valued 1 for all biographies (T1-T4) and 0 for the control group (T0). Column 1 depicts interest in all of the three possible STEM fields (Engineering, Computer Science, and Mathematics). Column 2 depicts interest in any of three possible STEM fields. Columns 3 to 5 depict interest in individual STEM field. The dependent variables are valued 1 for agreement and strong agreement on interest, and 0 otherwise. Each column reports estimates from a linear model. All estimates control for school socio-economic context and unbalanced covariates. Clustered standard errors by school are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.



Notes: This figure plots mean values and effect estimates on early interest in field. For each field, columns show mean values for the control group (T0) and the treatment group (T1-T4). Error bars correspond to the 95 percent confidence interval as estimated via OLS regression that includes school's socio-economic strata, unbalanced covariates, and clustered standard errors. Non-STEM fields (i.e., social work, culture, and art) are shown in softer color shades. Sample size is 1,017.

Figure 3: Treatment Effect on Early Interest in Professional Fields

Table 3: Treatment Effects by Subgroups

Subgroup	All	Girls	Boys	Poor	Non-poor	Low GPA	High GPA	Capital city	Others	STEM at T_0	Non-STEM at T_0
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Biography	.070**	.037	.093*	.060	.072*	.163***	-.002	-.120	.083**	-.014	.109***
	(.032)	(.037)	(.049)	(.047)	(.040)	(.061)	(.047)	(.070)	(.037)	(.053)	(.036)
Dep. var. mean	.23	.18	.29	.21	.24	.16	.27	.21	.24	.32	.19
Effect magn.	31%	20%	32%	29%	30%	102%	-1%	-57%	35%	-5%	57%
Diff. p-value	-	-	.334	-	-	-	.051	-	.008	-	.034
Observations	1,017	502	515	344	673	439	578	302	715	303	714
R^2	.006	.010	.015	.019	.006	.026	.009	.019	.013	.025	.019

Notes: This table reports the coefficients of treatment dummies on early interest in Engineering. The independent variables are computed as dummy valued 1 for all biographies (T1-T4) and 0 for the control group (T0). The dependent variables are valued 1 for agreement and strong agreement on interest in Engineering, and 0 otherwise. Column 1 shows the treatment effect for the whole sample. Columns 2 to 11 focus on a specific subgroup. Poor and Non-poor are constructed based on school's socio-economic context. Low and High GPA is split by median GPA of the year preceding the intervention. Baseline STEM status is constructed based on responses in the baseline survey. Each column reports estimates from a linear model. All estimates control for school socio-economic context and unbalanced covariates. Gender and GPA subgroup coefficients are tested for equality and the p-value is reported. Clustered standard errors by school are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table 4: Treatment Effects by Treatment Arms

	(1)	(2)	(3)	(4)	(5)
Biography (all)	.070**				
	(.032)				
Female Growth Mindset		.117**			
		(.043)			
Female No Growth Mindset			.032		
			(.052)		
Male Growth Mindset				.130***	
				(.036)	
Male No Growth Mindset					.106***
					(.033)
Dep. var. mean	.23	.23	.23	.23	.23
Effect magn.	31%	51%	14%	56%	46%
Diff. p-value	-	-	.161	-	.594
Observations	1,017	432	405	417	438
R^2	.006	.021	.020	.026	.033

Notes: This table reports the coefficients of treatment dummies on early interest in Engineering. The independent variables are computed as dummy valued 1 for treatments and 0 for the control group (`T0`). The dependent variables are valued 1 for agreement and strong agreement on interest in Engineering, and 0 otherwise. Column 1 shows the treatment effect for all biographies (`T1-T4`). Columns 2 to 5 focus on a each treatment arm. Each column reports estimates from a linear model. All estimates control for school socio-economic context and unbalanced covariates. Growth Mindset and Featured Gender subgroup coefficients are tested for equality and the p-value is reported. Clustered standard errors by school are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table 5: Treatment Effects by Biography Content

	(1)	(2)	(3)	(4)	(5)
Biography (all)	.070**				
	(.032)				
With Growth Mindset		.108***			
		(.035)			
No Growth Mindset			.055		
			(.037)		
Male Biography				.108***	
				(.030)	
Female Biography					.065
					(.043)
Dep. var. mean	.23	.23	.23	.23	.23
Effect magn.	31%	47%	24%	47%	28%
Diff. p-value	-	-	.205	-	.318
Observations	1,017	624	618	630	612
R^2	.006	.013	.013	.019	.007

Notes: This table reports the coefficients of treatment dummies on early interest in Engineering. The independent variables are computed as dummy valued 1 for treatments and 0 for the control group (`T0`). The dependent variables are valued 1 for agreement and strong agreement on interest in Engineering, and 0 otherwise. Column 1 shows the treatment effect for all biographies (`T1-T4`). Columns 2 to 5 focus on a specific type of biographies. Each column reports estimates from a linear model. All estimates control for school socio-economic context and unbalanced covariates. Growth Mindset and Featured Gender subgroup coefficients are tested for equality and the p-value is reported. Clustered standard errors by school are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table 6: Treatment Effects by Identity Match

	Gender		Ability	
	(1)	(2)	(3)	(4)
Matched Identity	.097**		.038	
	(.037)		(.047)	
Unmatched Identity		.063		.119***
		(.040)		(.026)
Dep. var. mean	.23	.23	.23	.23
Effect magn.	42%	27%	17%	52%
Observations	630	612	589	653
R^2	.016	.014	0.004	.023

Notes: This table reports the coefficients of treatment dummies on early interest in Engineering. The independent variables are computed as dummy valued 1 for treatments and 0 for the control group (T0). The first row variable focuses on biographies for which the sex/ability is the same as the student's. The second row variable focuses on biographies for which the sex/ability is not the same as the student's. The dependent variables are valued 1 for agreement and strong agreement on interest in Engineering, and 0 otherwise. Each column reports estimates from a linear model. All estimates control for school socio-economic context and unbalanced covariates. Matched Identity and Unmatched Identity coefficients are tested for equality and the p-value is reported. Clustered standard errors by school are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table 7: Mediation Analysis by Subgroups

	Base	Int. Eng.	Int. Eng.	Int. Eng.	Int. Eng.
	(1)	(2)	(3)	(4)	(5)
Panel A: Full Sample					
Biography	.070**	.061**	.057*	.070**	.051*
	(.032)	(.029)	(.032)	(.032)	(.029)
Baseline controls	✓	✓	✓	✓	✓
Self-comp.	-	✓	-	-	✓
Courses pref.	-	-	✓	-	✓
Beliefs	-	-	-	✓	✓
TE Change	-	-13%	-18%	-1%	-28%
Diff. p-value	-	.403	.100	.907	.172
R^2	.006	.165	.041	.007	.158
Observations	1,017	1,017	1,017	1,017	1,017
Panel B: Low GPA					
Biography	.163***	.159***	.160***	.161**	.152***
	(.061)	(.054)	(.058)	(.061)	(.053)
Baseline controls	✓	✓	✓	✓	✓
Self-comp.	-	✓	-	-	✓
Courses pref.	-	-	✓	-	✓
Beliefs	-	-	-	✓	✓
TE Change	-	-2%	-2%	-1%	-7%
Diff. p-value	-	.836	.791	.850	.634
R^2	.026	.192	.077	.031	.217
Observations	439	439	439	439	439
Panel C: Non-STEM at Baseline					
Biography	.109***	.088**	.088**	.110***	.073**
	(.036)	(.034)	(.038)	(.036)	(.034)
Baseline controls	✓	✓	✓	✓	✓
Self-comp.	-	✓	-	-	✓
Courses pref.	-	-	✓	-	✓
Beliefs	-	-	-	✓	✓
TE Change	-	-20%	-20%	1%	-33%
Diff. p-value	-	.058	.021	.891	.005
R^2	.019	.152	.057	.021	.172
Observations	714	714	714	714	714

Notes: This table reports the coefficients of treatment dummies on early interest in Engineering. The independent variables are computed as dummy valued 1 for treatments and 0 for the control group (T0). Panel A includes the full sample, Panel B only uses students with low GPA, and Panel C only uses students with no interest in STEM at baseline. Column 1 reports the baseline treatment effect. Columns 2 to 5 sequentially add potential mediating mechanisms: self-competence beliefs in Column 2, baseline task preference indices (math and verbal) in Column 3, gender and effort beliefs in Column 4, and all mediators jointly in Column 5. The dependent variables are valued 1 for agreement and strong agreement on interest in Engineering, and 0 otherwise. Each column reports estimates from a linear model. All estimates control for school socio-economic context and unbalanced covariates. Clustered standard errors by school are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

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A. Additional Results

Table A.1: Treatment Effects by Identity Match across Gender and Ability

	Girls	Boys	Low GPA	High GPA
	(1)	(2)	(3)	(4)
Matched Treatment	.041	.166***	.122	-.049
	(.040)	(.043)	(.078)	(.056)
Unmatched Treatment	.036	.089	.186***	.100***
	(.040)	(.063)	(.056)	(.033)
Dep. var. mean	.18	.29	.16	.26
Effect magn. (Matched)	23%	57%	75%	-19%
Effect magn. (Unmatched)	20%	31%	114%	38
Observations	502	515	439	575

Notes: This table reports the coefficients of treatment dummies on early interest in Engineering. The independent variables are computed as dummy valued 1 for treatments and 0 for the control group (T0). Columns 1 and 2 focus on matching of role model and student gender. Columns 3 and 4 focus on matching of role model and student ability, understanding as a match when low-GPa students are exposed to biographies with growth mindset and high-GPA students are exposed to biographies with no growth mindset. The dependent variables are valued 1 for agreement and strong agreement on interest in Engineering, and 0 otherwise. Each column reports estimates from a linear model. All estimates control for school socio-economic context and unbalanced covariates. Matched Identity and Unmatched Identity coefficients are tested for equality and the p-value is reported. Clustered standard errors by school are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table A.2: Biography Content: Growth Mindset

	STEM		Career		
	All	Any	Eng.	Coding	Maths
	(1)	(2)	(3)	(4)	(5)
Panel A. Biographies with Growth Mindset					
Biography (GM)	.054**	.025	.108***	.024	.024
	(.023)	(.045)	(.035)	(.051)	(.046)
Dep. var. mean	.08	.63	.23	.41	.34
Effect magn.	67%	4%	47%	6%	7%
Observations	624	624	624	624	624
R^2	.019	.012	.013	.025	.035
Panel B. Biographies without Growth Mindset					
Biography (No GM)	.028	-.030	.055	-.034	-.022
	(.021)	(.045)	(.037)	(.062)	(.052)
Dep. var. mean	.08	.63	.23	.41	.34
Effect magn.	35%	-5%	24%	-8%	-7%
Observations	618	618	618	618	618
R^2	.018	.021	.013	.022	.011
Panel C. Growth Mindset Differential					
Diff. due to GM	.019	.049	.034	.036	.056
	(.022)	(.049)	(.033)	(.048)	(.041)
Dep. var. mean	.1	.58	.28	.36	.32
Effect magn.	19%	8%	12%	10%	17%
Observations	792	792	792	792	792
R^2	.008	.010	.004	.013	.011

Notes: This table reports the coefficients of treatment dummies on different variables capturing interest in STEM fields. The independent variables are computed as dummy valued 1 for treatments and 0 for the control group. Panel A focuses on biographies with growth mindset (`T2` and `T4`) and uses the Emotions (`T0`) as the control group. Panel B focuses on the difference due to growth mindset on biographies (`T2` and `T4`) and uses biographies without growth mindset (`T1` and `T3`) as the control group. Column 1 depicts interest in all of the three possible STEM fields (Engineering, Computer Science, and Mathematics). Column 2 depicts interest in any of three possible STEM fields. Columns 3 to 5 depict interest in individual STEM field. The dependent variables are valued 1 for agreement and strong agreement on interest, and 0 otherwise. Each column reports estimates from a linear model. All estimates control for school socio-economic context and unbalanced covariates. Clustered standard errors by school are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table A.3: Biography Content: Gender

	STEM		Career		
	All	Any	Eng.	Coding	Maths
	(1)	(2)	(3)	(4)	(5)
Panel A. Female Biographies					
Biography	.027	.007	.065	.010	-.007
	(.024)	(.048)	(.043)	(.064)	(.051)
Dep. var. mean	.08	.63	.23	.41	.34
Effect magn.	34%	1%	28%	2%	-2%
Observations	612	612	612	612	612
R^2	.014	.010	.007	.020	.015
Panel B. Male Biographies					
Biography	.060**	.016	.108***	-.001	.024
	(.022)	(.044)	(.030)	(.055)	(.048)
Dep. var. mean	.08	.63	.23	.41	.34
Effect magn.	75%	3%	47%	0%	7%
Observations	630	630	630	630	630
R^2	.024	.021	.019	.024	.025
Panel C. Male Biographies Differential					
Diff. due to Male	.023	-.014	.020	-.010	.005
	(.020)	(.045)	(.034)	(.048)	(.038)
Dep. var. mean	.1	.6	.28	.37	.35
Effect magn.	23%	-2%	7%	-3%	1%
Observations	792	792	792	792	792
R^2	.009	.008	.003	.012	.009

Notes: This table reports the coefficients of treatment dummies on different variables capturing interest in STEM fields. The independent variables are computed as dummy valued 1 for treatments and 0 for the control group. Panel A focuses on female biographies (`T1` and `T2`) and uses the Emotions (`T0`) as the control group. Panel B focuses on male biographies (`T3` and `T4`) and uses the Emotions (`T0`) as the control group. Panel B focuses on male biographies (`T3` and `T4`) and uses female biographies (`T1` and `T2`) as the control group. Column 1 depicts interest in all of the three possible STEM fields (Engineering, Computer Science, and Mathematics). Column 2 depicts interest in any of three possible STEM fields. Columns 3 to 5 depict interest in individual STEM field. The dependent variables are valued 1 for agreement and strong agreement on interest, and 0 otherwise. Each column reports estimates from a linear model. All estimates control for school socio-economic context and unbalanced covariates. Clustered standard errors by school are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table A.4: Field Understanding and Self-Competence

	Understand	Self-competence	Understand	Self-competence
	(1)	(2)	(3)	(4)
Interested in ENG	.255***	.372***		
	(.079)	(.093)		
Boys			.042	.106*
			(.087)	(.054)
Non-Poor			-.090	-.003
			(.061)	(.041)
High GPA			.191**	-.050
			(.071)	(.048)
Dep. var. mean	.42	.12	-	-
Effect magn.	61%	310%	-	-
Observations	225	225	225	225
R^2	.110	.164	.098	.037

Notes: This table reports the coefficients of treatment dummies on understanding and perceived self-competence for the Engineering field. The independent variables are computed as dummy valued 1 for those interested in Engineering field, Boys, Non-Poor, and High GPA. The dependent variables are valued 1 for agreement and strong agreement on understanding/self-competence in Engineering, and 0 otherwise. Each column reports estimates from a linear model. All estimates control for school socio-economic context and unbalanced covariates. Clustered standard errors by school are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table A.5: Treatment Effects in Field Understanding and Self-Competence

	Understand	Self-competence	Understand	Self-competence
	(1)	(2)	(3)	(4)
Biography	.003	0.025		
	(.042)	(.030)		
With Growth Mindset			.026	.047
			(.057)	(.031)
Dep. var. mean	.49	.20	.49	.20
Effect magn.	1%	13%	5%	23%
Observations	1,017	1,017	624	624
R^2	.014	.005	.020	.012

Notes: This table reports the coefficients of treatment dummies on understanding and perceived self-competence for the Engineering field. The independent variables are computed as dummy valued 1 for treatments and 0 for the control group (T0). The first row variable focuses on all biographies (T1-T4). The second row variable focuses on biographies with growth mindset (T2 and T4). The dependent variables are valued 1 for agreement and strong agreement on understanding/self-competence in Engineering, and 0 otherwise. Each column reports estimates from a linear model. All estimates control for school socio-economic context and unbalanced covariates. Clustered standard errors by school are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table A.6: Mediation Analysis: Field Understanding and Self-Competence

	(1)	(2)	(3)	(4)
Biography	.070**	.060**	.070**	.061**
	(.032)	(.028)	(.031)	(.029)
Baseline controls	✓	✓	✓	✓
Self-competence	-	✓	-	✓
Understand	-	-	✓	✓
TE change	-	-14%	-.9%	-13%
Diff. p-value	-	.403	.942	.527
R^2	.006	.142	.059	.165
Observations	1,017	1,017	1,017	1,017

Notes: This table examines whether treatment effects on Engineering interest are mediated by field understanding and perceived self-competence. The main independent variables are computed as dummy valued 1 for all biographies (`T1-T4`) and 0 for the control group (`T0`) Mediator variables are valued 1 for agreement and strong agreement on understanding/self-competence in Engineering, and 0 otherwise. Column 1 refers to the main specification without mediators. Column 2 adds perceived self-competence as a mediator. Column 3 adds field understanding as a mediator. Column 4 includes both mediator variables jointly. Each column reports estimates from a linear model. All estimates control for school socio-economic context and unbalanced covariates. Standard errors clustered at the school level are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table A.7: Course Preferences

	Numerical	Verbal	Numerical	Verbal
	(1)	(2)	(3)	(4)
Interested in ENGI	1.048***	.421		
	(.315)	(.360)		
Boys			.380	-1.138**
			(.328)	(.393)
Non-Poor			-1.290	.017
			(.764)	(.634)
High GPA			.467	.357
			(.358)	(.441)
Dep. var. mean	3.75	3.79	-	-
Effect magn.	28%	11%	-	-
Observations	225	225	225	225
R^2	.091	.034	.071	.084

Notes: This table reports the coefficients of treatment dummies on numerical and verbal tasks preferences. The independent variables are computed as dummy valued 1 for those interested in Engineering field, Boys, Non-Poor, and High GPA. The dependent variables are based on 8 items assessing whether tasks are enjoyed, found interesting, loved during classes, loved as homework, considered enthusiastic, favorite, boring, or avoided for studying. Columns 1 to 4 depict numerical preferences through the aggregation of all 8 related items. Columns 5 to 8 depict verbal preferences through the aggregation of all 8 related items. Columns 1 and 4 depict preferences through the sum of all 8 items. Columns 2 and 5 depict preferences through any of the possible 8 items, and is valued 1 for agreement and strong agreement on interest, and 0 otherwise. Columns 3 and 6 depict preferences using an index from 0 to 1, where higher values are associated with stronger interest. Each column reports estimates from a linear model. All estimates control for school socioeconomic context and unbalanced covariates. Clustered standard errors by school are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table A.8: Treatment Effects in Course Preferences

	Numerical			Verbal		
	All	Any	Index	All	Any	Index
	(1)	(2)	(3)	(4)	(5)	(6)
Biography	.189	-.010	.140	.256	.012	.125
	(.222)	(.018)	(.088)	(.210)	(.025)	(.084)
Dep. var. mean	3.97	.93	-.12	3.92	.92	-.11
Effect magn.	5%	-1%	-	7%	1%	-
Observations	1,017	1,017	1,017	1,017	1,017	1,017
R^2	.026	.027	.039	.015	.022	.019

Notes: This table reports the coefficients of treatment dummies on numerical and verbal tasks preferences. The independent variables are computed as dummy valued 1 for all biographies (`T1-T4`) and 0 for the control group (`T0`). The dependent variables are based on 8 items assessing whether tasks are enjoyed, found interesting, loved during classes, loved as homework, considered enthusiastic, favorite, boring, or avoided for studying. Columns 1 to 4 depict numerical preferences through the aggregation of all 8 related items. Columns 5 to 8 depict verbal preferences through the aggregation of all 8 related items. Columns 1 and 4 depict interest through the sum of all 8 items. Columns 2 and 5 depict interest through any of the possible 8 items, and is valued 1 for agreement and strong agreement on interest, and 0 otherwise. Columns 3 and 6 depict interest using an index from 0 to 1, where higher values are associated with stronger interest. Each column reports estimates from a linear model. All estimates control for school socio-economic context and unbalanced covariates. Clustered standard errors by school are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table A.9: Mediation Analysis: Course Preferences

	Base	Math			Verbal		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Biography	.070**	.063*	.071**	.059*	.066**	.070**	.066**
	(.032)	(.032)	(.032)	(.032)	(.031)	(.032)	(.032)
Baseline controls	✓	✓	✓	✓	✓	✓	✓
Math All	-	✓	-	-	-	-	-
Math Any	-	-	✓	-	-	-	-
Math Index	-	-	-	✓	-	-	-
Verbal All	-	-	-	-	✓	-	-
Verbal Any	-	-	-	-	-	✓	-
Verbal Index	-	-	-	-	-	-	✓
TE change	-	-10%	2%	-17%	-7%	-.70%	-6%
Diff. p-value	-	.390	.554	.113	.254	.691	.223
R^2	.006	.045	.010	.040	.016	.007	.011
Observations	1,017	1,017	1,017	1,017	1,017	1,017	1,017

Notes: This table examines whether treatment effects on Engineering interest are mediated by course preferences. The main independent variables are computed as dummy valued 1 for all biographies (`T1-T4`) and 0 for the control group (`T0`). Mediator variables are based on 8 items assessing whether tasks are enjoyed, found interesting, loved during classes, loved as homework, considered enthusiastic, favorite, boring, or avoided for studying. Column 1 refers to the main specification without mediators. Columns 2 and 5 adds numerical and verbal preferences through the sum of all 8 items. Columns 3 and 6 adds numerical and verbal preferences through any of the possible 8 items, and is valued 1 for agreement and strong agreement on interest, and 0 otherwise. Columns 5 and 7 adds numerical and verbal preferences using an index from 0 to 1, where higher values are associated with stronger interest. Each column reports estimates from a linear model. All estimates control for school socio-economic context and unbalanced covariates. Clustered standard errors by school are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table A.10: Beliefs

(a) Effort beliefs

	Intel. can change (1)	Math can change (2)	Effort is Good (3)	Intel. can change (4)	Math can change (5)	Effort is Good (6)
Interested in ENGI	-.047	.063	.012			
	(.090)	(.052)	(.069)			
Boys				.054	-.066	-.105
				(.075)	(.050)	(.060)
Non-Poor				.169**	-.066	.197**
				(.063)	(.093)	(.069)
High GPA				-.066	.254**	.226***
				(.093)	(.092)	(.056)
Dep. var. mean	.37	.55	.66	-	-	-
Effect magn.	-13%	12%	2%	-	-	-
Observations	225	225	225	225	225	225
R^2	.043	.050	.066	.048	.104	.124

(b) Gender beliefs

	Explicit		Implicit	Explicit		Implicit
	Individual (1)	Social (2)	IAT (3)	Individual (4)	Social (5)	IAT (6)
Interested in ENGI	.040	-.087	-.093			
	(.026)	(.066)	(.052)			
Boys				.096***	.085*	-.046
				(.030)	(.045)	(.058)
Non-Poor				.057	-.063	-.002
				(.061)	(.088)	(.071)
High GPA				-.021	.025	.077**
				(.047)	(.074)	(.035)
Dep. var. mean	.06	.23	0	-	-	-
Effect magn.	67%	-38%	-	-	-	-
Observations	225	225	213	225	225	213
R^2	.042	.092	.050	.071	.096	.052

Notes: These tables report the coefficients of treatment dummies on beliefs. Panel A focuses on effort beliefs. Panel B focuses on gender beliefs. The independent variables are computed as dummy valued 1 for those interested in Engineering field, Boys, Non-Poor, and High GPA. Each column reports estimates from a linear model. All estimates control for school socio-economic context and unbalanced covariates. Clustered standard errors by school are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table A.11: Treatment Effects in Beliefs

(a) Effort beliefs

	Intel. can change (1)	Math can change (2)	Effort is Good (3)	Intel. can change (4)	Math can change (5)	Effort is Good (6)
Biography	-.029	-.086**	-.026			
	(.038)	(.043)	(.041)			
With Growth Mindset				-.072*	-.144***	-.023
				(.037)	(.047)	(.044)
Dep. var. mean	.36	.57	.67	.36	.57	.67
Effect magn.	-8%	-15%	-4%	-20%	-25%	-3%
Observations	1,017	1,017	1,017	624	624	624
R^2	.016	.023	.044	.020	.031	.070

(b) Gender beliefs

	Explicit		Implicit	Explicit		Implicit
	Individual (1)	Social (2)	IAT (3)	Individual (4)	Social (5)	IAT (6)
Biography	.044*	-.009	.013			
	(.025)	(.046)	(.032)			
Female Biography				.039	-.021	-.003
				(.026)	(.061)	(.032)
Dep. var. mean	.08	.21	-.02	.08	.21	-.02
Effect magn.	55%	-4%	-	49%	-10%	-
Observations	1,017	1,017	975	612	612	589
R^2	.014	.019	.018	.024	.034	.014

Notes: These tables report the coefficients of treatment dummies on beliefs. Panel A focuses on effort beliefs. Panel B focuses on gender beliefs. The independent variables are computed as dummy valued 1 for treatments and 0 for the control group (T0). The first row variable in both tables focuses on all biographies (T1-T4). The second row variable in Table **??** focuses on biographies with growth mindset (T2 and T4). The second row variable in Table **??** focuses on female biographies (T3 and T4). Each column reports estimates from a linear model. All estimates control for school socio-economic context and unbalanced covariates. Clustered standard errors by school are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table A.12: Mediation Analysis: Beliefs

	Base	Effort Beliefs				Gender Beliefs		All
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Biography	.070**	.070**	.070**	.070**	.071**	.070**	.069*	.070**
	(.032)	(.032)	(.032)	(.032)	(.032)	(.032)	(.036)	(.032)
Baseline controls	✓	✓	✓	✓	✓	✓	✓	✓
Intelligence can change	-	✓	-	-	-	-	-	✓
Math can change	-	-	✓	-	-	-	-	✓
Effort is good	-	-	-	✓	-	-	-	✓
Gender beliefs (Individual)	-	-	-	-	✓	-	-	✓
Gender beliefs (Social)	-	-	-	-	-	✓	-	✓
Implicit bias (IAT)	-	-	-	-	-	-	✓	-
TE change	-	0%	-1%	-1%	0%	0%	-2%	-1%
Diff. p-value	-	.801	.858	.610	.952	.978	.867	.907
R^2	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Observations	1,017	1,017	1,017	1,017	1,017	1,017	975	1,017

Notes: This table examines whether treatment effects on Engineering interest are mediated by effort and gender beliefs. The main independent variables are computed as dummy valued 1 for all biographies (T1-T4) and 0 for the control group (T0). Column 1 refers to the main specification without mediators. Column 2 adds a variable accounting for fixed intelligence, equal to 1 for agreement and strong agreement that intelligence is fixed, and 0 otherwise. Column 3 adds a variable accounting for fixed math ability, equal to 1 for agreement and strong agreement that math ability is fixed, and 0 otherwise. Column 4 adds a variable accounting for whether effort is good, equal to 1 for agreement and strong agreement, and 0 otherwise. Column 5 adds individual gender beliefs, equal to 1 for agreement and strong agreement that boys are better than girls in math, and 0 otherwise. Column 6 adds social gender beliefs, equal to 1 for agreement and strong agreement that classmates think boys are better than girls in math, and 0 otherwise. Column 7 adds the implicit association test (IAT) score, with higher values indicating greater gender bias toward science. Column 8 includes all mediators simultaneously, excluding the IAT. Each column reports estimates from a linear model. All estimates control for school socio-economic context and unbalanced covariates. Clustered standard errors by school are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table A.13: Treatment effects on Self-competence and Understanding by Subgroups

(a) Low GPA

	Self-competence (1)	Understood (2)	Self-competence (3)	Understood (4)
Biography	.015	.009		
	(.050)	(.045)		
With GM			.036	.018
			(.068)	(.057)
Dep. var. mean	.4	.23	.4	.23
Effect magn.	4%	4%	9%	8%
Observations	439	439	248	248
R^2	.014	.003	.011	.019

(b) No interested in STEM at baseline

	Self-competence (1)	Understood (2)	Self-competence (3)	Understood (4)
Biography	.054*	.035		
	(.027)	(.048)		
With GM			.081***	.071
			(.026)	(.064)
Dep. var. mean	.17	.45	.17	.45
Effect magn.	32%	8%	48%	16%
Observations	714	714	447	447
R^2	.011	.012	.022	.019

Notes: These tables report the coefficients of treatment dummies on self-competence and understanding. Table A.13a focuses on low GPA students. Table A.13b focuses on students with no prior interest in STEM. The independent variables are computed as dummy valued 1 for those interested in Engineering field. First row presents results using a dummy valued 1 for all biographies (`T1`-`T4`) and 0 for the control group (`T0`). Second row presents results using a dummy valued 1 for growth mindset bios (`T2` and `T4`) and 0 for the control group (`T0`). Each column reports estimates from a linear model. All estimates control for school socio-economic context and unbalanced covariates. Clustered standard errors by school are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table A.14: Treatment effects on course preferences by subgroups

(a) Low GPA

	Math interest			Verbal interest			Math interest			Verbal interest		
	All	Any	Index	All	Any	Index	All	Any	Index	All	Any	Index
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Biography	-.116	-.033	.061	.322	.017	.177						
	(.239)	(.024)	(.110)	(.362)	(.035)	(.138)						
Growth Mindset							-.270	-.057*	.001	.377	.008	.184
							(.292)	(.029)	(.113)	(.440)	(.045)	(.165)
Dep. var. mean	3.81	.95	-.18	3.71	.93	-.2	3.81	.95	-.18	3.71	.93	-.2
Effect magn.	-3%	-4%	-	9%	2%	-	-7%	-6%	-	10%	1%	-
Observations	439	439	439	439	439	439	248	248	248	248	248	248
R^2	.031	.026	.043	.036	.021	.037	.081	.055	.103	.039	.019	.036

(b) No interested in STEM at baseline

	Math interest			Verbal interest			Math interest			Verbal interest		
	All	Any	Index	All	Any	Index	All	Any	Index	All	Any	Index
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Biography	.396	.008	.218**	.265	.020	.154						
	(.240)	(.019)	(.092)	(.222)	(.031)	(.093)						
Growth Mindset							.406	-.001	.218**	.299	.006	.123
							(.246)	(.018)	(.090)	(.249)	(.038)	(.109)
Dep. var. mean	3.79	.93	-.18	3.84	.93	-.15	3.79	.93	-.18	3.84	.93	-.15
Effect magn.	10%	1%	-	7.%	2%	-	11%	0%	-	8%	1%	-
Observations	714	714	714	714	714	714	447	447	447	447	447	447
R^2	.027	.029	.047	.022	.016	.027	.062	.051	.093	.019	.012	.019

Notes: These tables report the coefficients of treatment dummies on course preferences. Table A.14a focuses on low GPA students. Table A.14b focuses on students with no prior interest in STEM. The independent variables are computed as dummy valued 1 for those interested in Engineering field. Column 1 to 6 presents results using a dummy valued 1 for all biographies (T1-T4) and 0 for the control group (T0). Column 6 to 12 presents results using a dummy valued 1 for growth mindset bios (T2 and T4) and 0 for the control group (T0). Each column reports estimates from a linear model. All estimates control for school socio-economic context and unbalanced covariates. Clustered standard errors by school are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table A.15: Treatment effects on Beliefs by Subgroups

(a) Low GPA

	Biography					Growth Mindset				
	Intel. change	Math change	Effort is good	Better boys (me)	Better Boys (Soc)	InteL. change	Math change	Effort is good	Better Boys (Me)	Better Boys (Soc)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Biography	-.115**	.018	-.023	.027	-.068					
	(.050)	(.072)	(.062)	(.040)	(.051)					
Growth Mindset						-.192***	-.043	-.034	.048	-.007
						(.052)	(.082)	(.076)	(.038)	(.063)
Dep. var. mean	.37	.42	.51	.08	.22	.37	.42	.51	.08	.22
Effect magn.	-31%	4%	-4%	34%	-31%	-52%	-10%	-7%	59%	-3%
Observations	439	439	439	439	439	248	248	248	248	248
R^2	.011	.032	.041	.012	.041	.034	.030	.052	.022	.089

(b) No interested in STEM at baseline

	Biography					Growth Mindset				
	Intel. change	Math change	Effort is good	Better boys (me)	Better Boys (Soc)	InteL. change	Math change	Effort is good	Better Boys (Me)	Better Boys (Soc)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Biography	-.045	-.108***	.022	.036	-.012					
	(.038)	(.037)	(.052)	(.033)	(.049)					
Growth Mindset						-.081**	-.160***	.022	.084***	.049
						(.035)	(.046)	(.056)	(.029)	(.063)
Dep. var. mean	.35	.57	.61	.09	.21	.35	.57	.61	.09	.21
Effect magn.	-13%	-19%	4%	41%	-6%	-23%	-28%	4%	93%	24%
Observations	714	714	714	714	714	447	447	447	447	447
R^2	.027	.033	.036	.017	.011	.019	.032	.050	.033	.017

Notes: These tables report the coefficients of treatment dummies on beliefs. Table A.15a focuses on low GPA students. Table A.15b focuses on students with no prior interest in STEM. The independent variables are computed as dummy valued 1 for those interested in Engineering field. Column 1 to 5 presents results using a dummy valued 1 for all biographies (`T1-T4`) and 0 for the control group (`T0`). Column 6 to 10 presents results using a dummy valued 1 for growth mindset bios (`T2` and `T4`) and 0 for the control group (`T0`). Each column reports estimates from a linear model. All estimates control for school socio-economic context and unbalanced covariates. Clustered standard errors by school are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table A.16: Biography Content: Growth Mindset for Students with no prior interest in STEM

	STEM		Career		
	All	Any	Eng.	Coding	Maths
	(1)	(2)	(3)	(4)	(5)
Panel A. Biographies with Growth Mindset					
Biography (GM)	0.080***	0.050	0.166***	0.061	0.030
	(0.022)	(0.048)	(0.040)	(0.052)	(0.045)
Dep. var. mean	.07	.61	.19	.37	.34
Effect magn.	115%	8%	87%	17%	9%
Observations	447	447	447	447	447
R^2	0.024	0.014	0.031	0.035	0.036
Panel B. Biographies without Growth Mindset					
Biography (No GM)	0.050**	-0.010	0.070*	0.053	-0.022
	(0.019)	(0.054)	(0.038)	(0.071)	(0.060)
Dep. var. mean	.07	.61	.19	.37	.34
Effect magn.	72%	-2%	37%	14%	-6%
Observations	427	427	427	427	427
R^2	0.030	0.018	0.031	0.029	0.008
Panel C. Growth Mindset Differential					
Diff. due to GM	0.023	0.068	0.074**	0.010	0.061
	(0.025)	(0.049)	(0.034)	(0.046)	(0.043)
Dep. var. mean	.12	.58	.28	.4	.34
Effect magn.	19%	12%	26%	2%	18%
Observations	554	554	554	554	554
R^2	0.015	0.014	0.014	0.020	0.010

Notes: This table reports the coefficients of treatment dummies on different variables capturing interest in STEM fields. The independent variables are computed as dummy valued 1 for treatments and 0 for the control group. Panel A focuses on biographies with growth mindset (`T2` and `T4`) and uses the Emotions (`T0`) as the control group. Panel B focuses on the difference due to growth mindset on biographies (`T2` and `T4`) and uses biographies without growth mindset (`T1` and `T3`) as the control group. Column 1 depicts interest in all of the three possible STEM fields (Engineering, Computer Science, and Mathematics). Column 2 depicts interest in any of three possible STEM fields. Columns 3 to 5 depict interest in individual STEM field. The dependent variables are valued 1 for agreement and strong agreement on interest, and 0 otherwise. Each column reports estimates from a linear model. All estimates control for school socio-economic context and unbalanced covariates. Clustered standard errors by school are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table A.17: Biography Content: Growth Mindset for students with low GPA

	STEM		Career		
	All	Any	Eng.	Coding	Maths
	(1)	(2)	(3)	(4)	(5)
Panel A. Biographies with Growth Mindset					
Biography (GM)	0.062	-0.067	0.122	0.035	-0.099
	(0.044)	(0.073)	(0.078)	(0.063)	(0.083)
Dep. var. mean	.06	.62	.16	.41	.33
Effect magn.	103%	-11%	76%	9%	-30%
Observations	248	248	248	248	248
R^2	0.041	0.020	0.041	0.033	0.046
Panel B. Biographies without Growth Mindset					
Biography (No GM)	0.073**	0.028	0.186***	0.021	-0.021
	(0.030)	(0.082)	(0.056)	(0.074)	(0.080)
Dep. var. mean	.06	.62	.16	.41	.33
Effect magn.	122%	5%	116%	5%	-6%
Observations	277	277	277	277	277
R^2	0.040	0.016	0.055	0.024	0.014
Panel C. Growth Mindset Differential					
Diff. due to GM	0.010	-0.016	-0.020	0.010	0.013
	(0.035)	(0.080)	(0.049)	(0.066)	(0.066)
Dep. var. mean	.13	.6	.32	.39	.33
Effect magn.	8%	-3%	-6%	3%	4%
Observations	353	353	353	353	353
R^2	0.010	0.018	0.011	0.014	0.010

Notes: This table reports the coefficients of treatment dummies on different variables capturing interest in STEM fields. The independent variables are computed as dummy valued 1 for treatments and 0 for the control group. Panel A focuses on biographies with growth mindset (`T2` and `T4`) and uses the Emotions (`T0`) as the control group. Panel B focuses on the difference due to growth mindset on biographies (`T2` and `T4`) and uses biographies without growth mindset (`T1` and `T3`) as the control group. Column 1 depicts interest in all of the three possible STEM fields (Engineering, Computer Science, and Mathematics). Column 2 depicts interest in any of three possible STEM fields. Columns 3 to 5 depict interest in individual STEM field. The dependent variables are valued 1 for agreement and strong agreement on interest, and 0 otherwise. Each column reports estimates from a linear model. All estimates control for school socio-economic context and unbalanced covariates. Clustered standard errors by school are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table A.18: Biography Content: Gender for students with low GPA

	STEM		Career		
	All	Any	Eng.	Coding	Maths
	(1)	(2)	(3)	(4)	(5)
Panel A. Female Biographies					
Biography	0.043	-0.043	0.151**	-0.005	-0.088
	(0.036)	(0.078)	(0.067)	(0.074)	(0.080)
Dep. var. mean	.06	.62	.16	.41	.33
Effect magn.	72%	-7%	94%	-1%	-27%
Observations	249	249	249	249	249
R^2	0.025	0.019	0.034	0.035	0.033
Panel B. Male Biographies					
Biography	0.109***	0.038	0.194***	0.073	0.005
	(0.034)	(0.069)	(0.060)	(0.062)	(0.082)
Dep. var. mean	.06	.62	.16	.41	.33
Effect magn.	181%	6%	122%	18%	1%
Observations	276	276	276	276	276
R^2	0.037	0.019	0.053	0.023	0.030
Panel C. Male Biographies Differential					
Diff. due to Male	0.041	0.077	-0.011	0.073	0.086
	(0.033)	(0.066)	(0.048)	(0.058)	(0.054)
Dep. var. mean	.11	.55	.32	.35	.29
Effect magn.	38%	14%	-3%	21%	30%
Observations	353	353	353	353	353
R^2	0.013	0.024	0.010	0.019	0.017

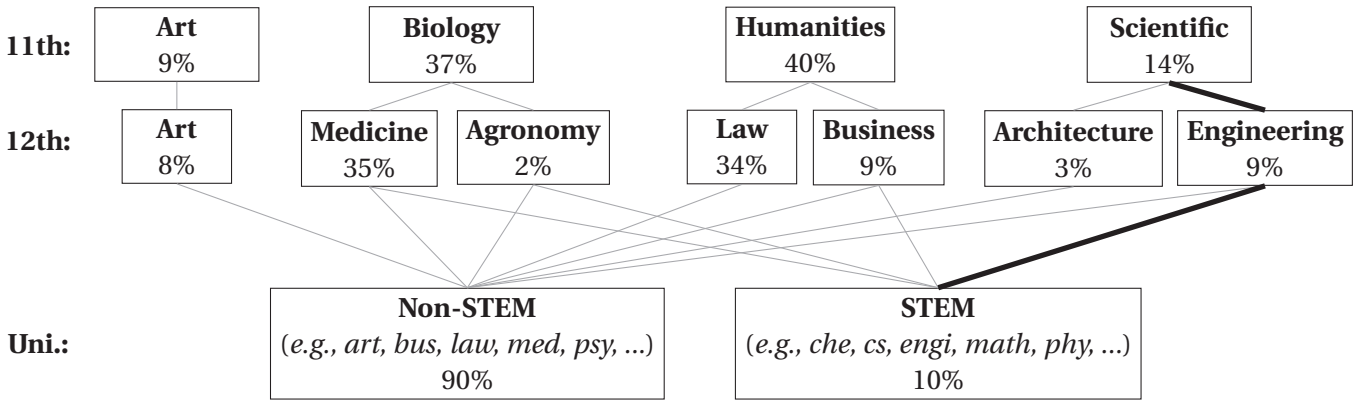
Notes: This table reports the coefficients of treatment dummies on different variables capturing interest in STEM fields. The independent variables are computed as dummy valued 1 for treatments and 0 for the control group. Panel A focuses on female biographies (`T1` and `T2`) and uses the Emotions (`T0`) as the control group. Panel B focuses on male biographies (`T3` and `T4`) and uses the Emotions (`T0`) as the control group. Panel B focuses on male biographies (`T3` and `T4`) and uses female biographies (`T1` and `T2`) as the control group. Column 1 depicts interest in all of the three possible STEM fields (Engineering, Computer Science, and Mathematics). Column 2 depicts interest in any of three possible STEM fields. Columns 3 to 5 depict interest in individual STEM field. The dependent variables are valued 1 for agreement and strong agreement on interest, and 0 otherwise. Each column reports estimates from a linear model. All estimates control for school socio-economic context and unbalanced covariates. Clustered standard errors by school are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table A.19: Biography Content: Gender for Students with no prior interest in STEM

	STEM		Career		
	All	Any	Eng.	Coding	Maths
	(1)	(2)	(3)	(4)	(5)
Panel A. Female Biographies					
Biography	0.052**	0.015	0.109**	0.061	-0.012
	(0.023)	(0.054)	(0.047)	(0.066)	(0.057)
Dep. var. mean	.07	.61	.19	.37	.34
Effect magn.	74%	3%	58%	16%	-4%
Observations	441	441	441	441	441
R^2	0.023	0.017	0.023	0.034	0.013
Panel B. Male Biographies					
Biography	0.087***	0.058	0.143***	0.072	0.043
	(0.021)	(0.051)	(0.036)	(0.060)	(0.053)
Dep. var. mean	.07	.61	.19	.37	.34
Effect magn.	125%	9%	75%	20%	13%
Observations	433	433	433	433	433
R^2	0.029	0.020	0.031	0.033	0.020
Panel C. Male Biographies Differential					
Diff. due to Male	0.023	0.020	0.002	0.020	0.039
	(0.022)	(0.040)	(0.040)	(0.040)	(0.044)
Dep. var. mean	.12	.59	.31	.38	.35
Effect magn.	19%	3%	1%	5%	11%
Observations	554	554	554	554	554
R^2	0.015	0.011	0.009	0.021	0.009

Notes: This table reports the coefficients of treatment dummies on different variables capturing interest in STEM fields. The independent variables are computed as dummy valued 1 for treatments and 0 for the control group. Panel A focuses on female biographies (`T1` and `T2`) and uses the Emotions (`T0`) as the control group. Panel B focuses on male biographies (`T3` and `T4`) and uses the Emotions (`T0`) as the control group. Panel B focuses on male biographies (`T3` and `T4`) and uses female biographies (`T1` and `T2`) as the control group. Column 1 depicts interest in all of the three possible STEM fields (Engineering, Computer Science, and Mathematics). Column 2 depicts interest in any of three possible STEM fields. Columns 3 to 5 depict interest in individual STEM field. The dependent variables are valued 1 for agreement and strong agreement on interest, and 0 otherwise. Each column reports estimates from a linear model. All estimates control for school socio-economic context and unbalanced covariates. Clustered standard errors by school are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

B. Descriptive Statistics



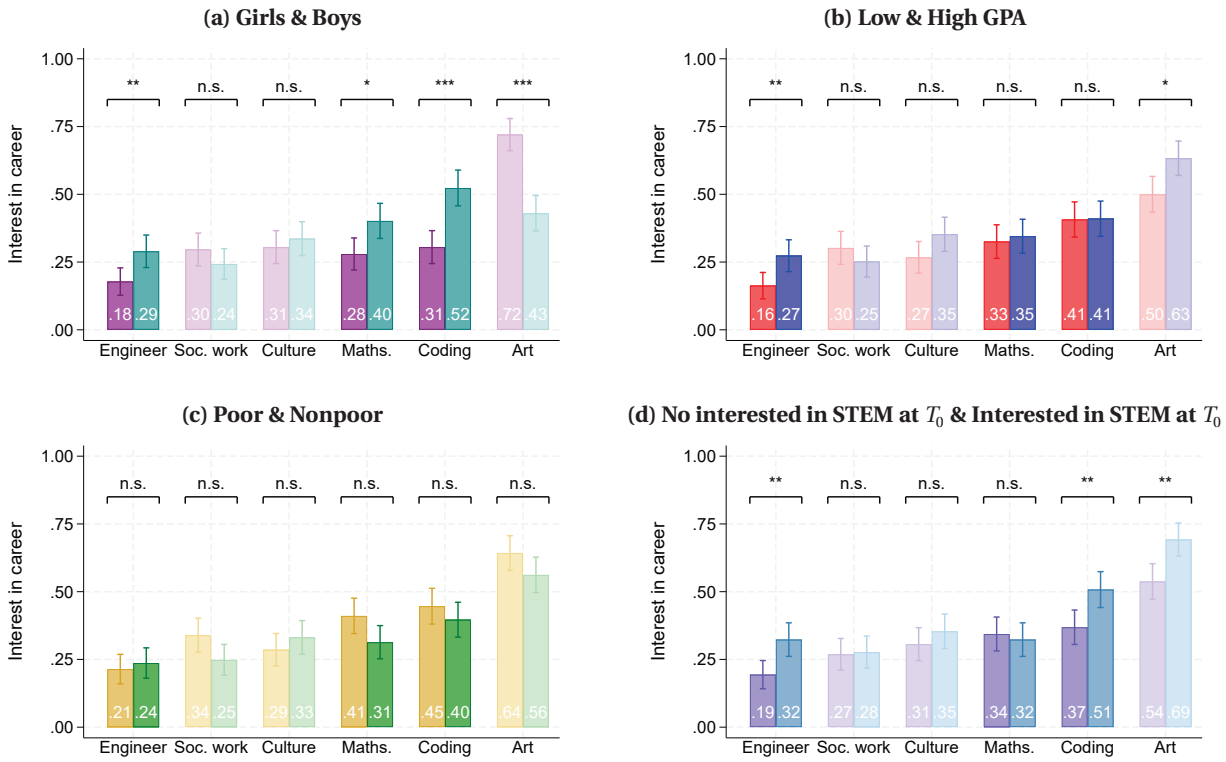
Notes: These figures shows the STEM pipeline from late high school to university. Each box shows the possible tracks and the share of students in each, within each grade. All students complete the same coursework up to 10th grade. In 11th grade, students choose one of four primary tracks: Art, Biology, Humanities, or Scientific. Scientific is the most math-intensive track. In 12th grade, students select an endline track based on their 11th-grade track. Students in the Art track continue to Art. Students in the Biology track choose between Medicine or Agronomy. Students in the Humanities track choose between Law or Business. Students in the Scientific track choose between Architecture or Engineering. Engineering is the most math-intensive endline track. Figures show the share of students within each grade in high school and within university enrollments in the public educational system, and are computed using public registry data from *Consejo de Educación Secundaria* and *Universidad de la República*.

Figure B.1: STEM pipeline in Uruguay

Table B.1: Descriptive Statistics by STEM interest at baseline

	Mean	Others	Diff.
	(1)	(2)	(3)
Girls (vs. Boys)	.39	.21	.19***
	(.49)	(.40)	(.03)
Low-GPA (vs. High-GPA)	.24	.34	.10***
	(.47)	(.43)	(.03)
Poor (vs. Non-poor)	.24	.33	-.09***
	(.43)	(.47)	(.03)
Capital City (vs. Others)	.30	.29	.00
	(.46)	(.46)	(.03)

Notes: This table reports initial interest in STEM. Columns 1 and 2 report the mean share of students for different group, with standard deviations in parentheses. Column 3 reports the difference in means between groups in column 1 and 2, with standard errors in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.



Notes: These figures plot mean values on early interest in professional fields. Sample is composed only by student participating in the emotions project (T0). Sample size is 1,017. For each field, columns show mean values for two subgroups. Subfigure A compares by gender: the first bar shows values for girls and the second bar shows values for boys. Subfigure B compares by previous year GPA: the first bar shows values below the mean and the second bar shows values above the mean. Subfigure C compares by socio-economic context: the first bar shows values for students from low SES and the second bar for students from high SES. Subfigure D compares by baseline STEM interest: the first bar shows vlues for students wit prior interst in STEM and the second bar for stuents with no prior interst in STEM. Error bars correspond to 95% confidence intervals. Non-STEM fields (i.e., social work, culture, and art) are shown in softer color shades.

Figure B.2: Early Interest in Fields

C. Experimental Details

Table C.1: Balance checks for students

	Control			Treatment			Diff.
	N	Mean	SD	N	Mean	SD	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	225	.48	.50	792	.52	.50	.046
Age	225	11.14	.79	792	11.02	.79	-.185
Lives with both parents	225	.62	.49	792	.62	.49	.001
Sibilings (#)	225	2.10	1.57	792	2.12	2.08	.020
Educated caregiver	153	.46	.50	528	.35	.48	-.082*
Occupied caregiver	217	.47	.50	767	.48	.50	.005
Good using PC	225	.62	.49	792	.66	.47	.045
Good using keyboard	225	.73	.44	792	.70	.46	-.027
Good using mobile and tablets	225	.81	.39	792	.84	.37	.031
Good in Scratch	225	.59	.49	792	.62	.49	.049
Good in CT	225	.70	.46	792	.65	.48	-.053
Good searching in internet	225	.69	.46	792	.71	.45	.034

Notes: This table compares baseline characteristics between the control and treatment groups. Caregiver's education is coded as 1 for those with high educational attainment, and 0 otherwise. Skills for PC, keyboard, mobile and tablets, Scratch, CT, and searching internet are self-reported. Columns 1 to 3 show baseline characteristics for the control group (`T0`). Columns 4 to 6 show baseline characteristics for the the treatment group, combined across four treatment arms (`T1`-`T4`). Columns 1 and 4 depicts the sample size. Columns 2 and 5 depicts the variable mean. Columns 3 and 6 depicts the variable standard deviation. Column 7 depicts the difference between the control and treatment groups. Clustered standard errors by school are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table C.2: Balance checks for teachers

	Control			Treatment			Diff.
	N	Mean	SD	N	Mean	SD	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. Teacher							
Age	12	39.17	7.65	47	42.66	8.39	3.695
Teacher educational level	12	.08	.29	47	.06	.25	-.016
Experience (years)	12	12.58	7.96	47	15.40	9.00	3.348
Experience in school (years)	12	6.17	6.35	47	5.04	5.55	-.984
Experience in CT (years)	12	3.00	1.60	47	2.38	1.47	-.627
Weekly class preparation (hours)	12	8.42	5.60	47	8.34	4.37	.052
Math preference	12	3.75	1.22	47	4.40	.80	.651*
Verbal preference	12	4.25	1.06	47	4.23	.70	-.006
Science preference	12	3.92	1.38	47	4.30	.62	.332
Social science preference	12	4.00	1.28	47	4.06	.99	.088
CT preference	12	3.67	.78	47	3.77	.84	.055
Panel B. Remote							
Sex	12	.50	.52	47	.30	.46	-.227
Age	12	37.67	11.28	47	44.00	9.95	6.970**
Experience in school (years)	12	1.00	1.04	47	.74	.71	-.236
Experience in CT (years)	12	3.08	1.98	47	2.85	1.91	-.056
Weekly class preparation (hours)	12	6.17	5.39	47	4.20	4.43	-1.768
Share of boys in class	12	.34	.11	47	.37	.14	.041

Notes: This table compares baseline characteristics of teachers and remote instructors between the control and treatment groups. Columns 1 to 3 show baseline characteristics for the control group (`T0`). Columns 4 to 6 show baseline characteristics for the the treatment group, combined across four treatment arms (`T1`-`T4`). Columns 1 and 4 depicts the sample size. Columns 2 and 5 depicts the variable mean. Columns 3 and 6 depicts the variable standard deviation. Column 7 depicts the difference between the control and treatment groups. Clustered standard errors by school are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

D. Deviations from the Pre-Analysis Plan

This appendix lists the differences between the pre-analysis plan registered at the AEA RCT Registry (AEARCTR-0013425) and the study as implemented and reported.

Implementation. The plan describes biographies of scientists. The biographies we use depict two fictional professional working in STEM. The plan schedules a six-week intervention that starts in the first week of May and runs in the same weeks for all classes. It schedules the students' baseline survey in that first week and the endline survey in June. The intervention consisted of eight weekly sessions. Most classes ran them from May 6 to July 22, and the classes that started later finished by September 16. Students answered the endline survey from September 6 to September 27 (see Figure 1).

Sample. The plan expects 60 schools, 12 per treatment arm, and 2,640 students. Our sample has 53 schools, 59 classes, and 1,401 students, of whom 1,017 answered both surveys (see Figure 2). The plan excludes only students who do not participate in the endline survey. We also exclude two classes, one without an assigned remote instructor and one whose teacher completed no survey or monitoring activity. We further exclude students who did not answer the baseline survey.

Outcomes. The plan focuses in overall interest in STEM, defined as the sum of interest in Engineering, Computer Science, and Mathematics over the sum of interest in all fields. We report binary indicators for interest in all three STEM fields, in any STEM field, and in each field separately (see Table 2). From Table 3 onward, the analysis centers in interest in Engineering alone. We chose this focus after observing that the effect in Table 2 is concentrated in Engineering. The plan does not single out any field. The plan also registers preferences for mathematics as a main outcome and as a robustness check, and confidence in STEM jobs as a secondary outcome. We report preferences for numerical tasks as a potential mechanism and not as an outcome, built from eight items instead of the registered nine. We report perceived self-competence only for Engineering (see Table A.5).

Specification. The plan tests each hypothesis first with unconditional t-tests and with regressions without controls, and then adds students' age and gender, teacher characteristics, and school fixed effects. School fixed effects cannot be estimated, because the treatment varies at the school level. All our estimates control for the school's socio-economic context, the age of the teacher and of the remote instructor, and the teacher's preference for mathematics. We selected the three educator controls after inspecting baseline balance (see Table C.2). We do not report estimates without controls.

Heterogeneity and mechanisms. The plan registers heterogeneity in every hypothesis by students' gender and by mathematics performance, splitting students at the class median score of a mathematics quiz. We measure ability with the GPA of the previous year, instead of using a mathematics quiz. Heterogeneity by school socio-economic context and by baseline interest in STEM is not registered. The plan states two expectations on identity. The first is that the effect is larger when students share the gender of the character. The second is that biographies with growth mindset are a stronger role model for students

with low mathematics performance. The plan names beliefs on growth mindset, gender stereotypes, and confidence as channels. The use of field understanding and course preferences as mediators, are not registered.

E. Control and Interventions

This appendix describes the two projects used in the experiment, based on the teacher guides developed by Ceibal for its Computational Thinking program: *Escribe tu propia aventura* for the Biography projects (T1–T4) and *AnimoCiones* for the Emotions project (T0). Guides were provided to the classroom teacher and the remote instructor of each class. Both projects are organized in six stages, combine classroom activities led by the teacher with weekly video sessions led by the remote instructor, and cover comparable programming concepts. The Biography guides are identical except for the story that students turn into an animation.

We include an explanation of the Emotions project and English-translated versions of each biography story guide.

E.1. Emotions (T0)

The Emotions project has no given story and no given character. Students are the main character of their own animation, and they write its content themselves. In the first scene, the character introduces itself with a short text in first person about the student's own traits and tastes. In the second scene, the character tells what emotions it feels. The animation then splits in two, with one scene for each of two emotions that the student chooses. In an optional last step, students add to each scene what triggers the emotion. The teacher guide gives no example script, and Table E.1 reports the prompts it gives the teacher to start the discussion in class.

E.2. Male Biography without Growth Mindset (T1)

In a small town lived a boy named Juan. Every day he put on his white smock and blue bow to go to school.[13] Like any other boy his age, he greatly enjoyed recess, where he could run and play with his friends without a care. When it came to math classes, every problem was a new adventure.

At school, Juan solved math challenges that seemed complex with great ease, and he was always willing to help his classmates. Every time the teacher explained a new topic, he felt that numbers were like a building game in which all the pieces fit together perfectly. Juan felt that the math adventure allowed him to see the world in a different way, full of possibilities.

As he grew up, he discovered his passion for solving problems and working with numbers. He immersed himself in the world of informatics and computer science, where numbers were the basis of everything. He excelled in his career, solving complex problems and developing new technologies. His ability to understand mathematics had not only helped him at school, but had also opened the doors to a bright future.

In the end, Juan succeeded in his professional life, becoming an expert. He fondly remembered his math classes, where he found the key to his success. Through his passion, he inspired others to embark on the world of numbers.

[13] In Uruguay, public primary school students wear a white smock with a large blue bow.

E.3. Male Biography with Growth Mindset (T2)

In a small town lived a boy named Juan. Every day he put on his white smock and blue bow to go to school. Like any other boy his age, he greatly enjoyed recess, where he could run and play with his friends without a care. However, when it came to math, Juan did not feel so confident. Numbers seemed to get tangled in his mind, and every class became a challenge.

One day, during a math class, something extraordinary happened. While his teacher was explaining a complicated problem, suddenly everything seemed to fall into place in his mind. The pieces of the math puzzle lined up, and he began to understand the concepts clearly. This new understanding did not come out of nowhere: with the support and encouragement of his teacher, Juan had begun to understand a little more. From that day on, he decided to try harder, to be more persistent, to work hard, and not to get discouraged. When he did not understand something, he thought it was not a problem, because he could ask questions and look for help in order to learn and understand what he found most difficult.

As he grew up, he discovered his passion for solving problems and working with numbers. He immersed himself in the world of informatics and computer science, where numbers were the basis of everything. With effort and dedication, he excelled in his career, solving complex problems and developing new technologies. His ability to understand mathematics had not only helped him at school, but had also opened the doors to a bright future.

In the end, Juan succeeded in his professional life, becoming an expert. He fondly remembered that day when everything changed in math class, where he found the key to his success. Through his determination and passion for numbers, he showed that many obstacles can be overcome with perseverance and effort.

E.4. Female Biography without Growth Mindset (T3)

In a small town lived a girl named Maria. Every day she put on his white smock and blue bow to go to school. Like any other girl his age, she greatly enjoyed recess, where he could run and play with her friends without a care. When it came to math classes, every problem was a new adventure.

At school, Maria solved math challenges that seemed complex with great ease, and she was always willing to help his classmates. Every time the teacher explained a new topic, she felt that numbers were like a building game in which all the pieces fit together perfectly. Maria felt that the math adventure allowed her to see the world in a different way, full of possibilities.

As she grew up, she discovered her passion for solving problems and working with numbers. She immersed herself in the world of informatics and computer science, where numbers were the basis of everything. She excelled in her career, solving complex problems and developing new technologies. Her ability to understand mathematics had not only helped her at school, but had also opened the doors to a bright future.

In the end, Maria succeeded in her professional life, becoming an expert. She fondly remembered her math classes, where she found the key to his success. Through her passion, she inspired others to embark on the world of numbers.

E.5. Female Biography with Growth Mindset (T4)

In a small town lived a girl named Maria. Every day she put on her white smock and blue bow to go to school. Like any other girl her age, she greatly enjoyed recess, where she could run and play with her friends without a care. However, when it came to math, Maria did not feel so confident. Numbers seemed to get tangled in her mind, and every class became a challenge.

One day, during a math class, something extraordinary happened. While her teacher was explaining a complicated problem, suddenly everything seemed to fall into place in her mind. The pieces of the math puzzle lined up, and she began to understand the concepts clearly. This new understanding did not come out of nowhere: with the support and encouragement of her teacher, Maria had begun to understand a little more. From that day on, she decided to try harder, to be more persistent, to work hard, and not to get discouraged. When she did not understand something, she thought it was not a problem, because she could ask questions and look for help in order to learn and understand what she found most difficult.

As she grew up, she discovered her passion for solving problems and working with numbers. She immersed herself in the world of informatics and computer science, where numbers were the basis of everything. With effort and dedication, she excelled in her career, solving complex problems and developing new technologies. Her ability to understand mathematics had not only helped her at school, but had also opened the doors to a bright future.

In the end, Maria succeeded in her professional life, becoming an expert. She fondly remembered that day when everything changed in math class, where she found the key to her success. Through her determination and passion for numbers, she showed that many obstacles can be overcome with perseverance and effort.

Table E.1: Scenes and Example Prompts in the Teacher Guide of the Emotions Project

Scene	Content	Prompts for the discussion in class
1	The character introduces itself	Name or nickname, age, activities the student likes, and where the student is.
2	The character tells what it feels	"I feel fear when I am home alone and I hear a noise." "I feel happy because my football team won the final." "Every time I learn I have a test, I feel very nervous."
3	One scene for each of two emotions	Students recall in which situation they felt each emotion and describe the surroundings.
Optional	What triggers each emotion	"When my mom makes me a cake, I feel joy." "When I get a bad grade, I feel sad." "When I think about ghosts, I feel fear."

F. Questionnaires

We include English-translated versions of the questionnaires used to collect data.

F.1. Teacher

F.1.1. Baseline Survey

Good morning:

As part of your participation in the Computational Thinking Narratives project developed by Ceibal with external researchers, we ask you to answer a few brief questions. The questionnaire takes no more than 10 minutes. Thank you very much for your collaboration!

First, we will ask you some general questions about yourself:

1. Number of the school where you work with this 5th grade group
   `Space to fill in the school number`
2. 5th grade group you are participating with
   `Drop-down list with A, B, C, D`
3. Could you indicate the department where the school is located?
   `Drop-down list with Montevideo and Canelones`
4. What is your age?
   `Space to write a number between 20 and 70`
5. What is your highest educational level achieved? Please answer for the one you have completed.
   (Primary teaching degree, Other teaching degree (professorship, social education, etc.), other tertiary studies, University undergraduate degree, University postgraduate degree.)
6. How many years have you been teaching?
   (Space to fill with a number)
7. How many years have you worked at this school?
   (Space to fill with a number)
8. On average, how many hours a week do you dedicate to lesson preparation?
   (Space to fill with a number)
9. Is this your first time participating in the Computational Thinking project?
   (Two options: Yes, No.)
10. If the answer is Yes, how many times have you participated?

To finish, we will ask you questions about your preferences when teaching.

In which areas do you feel most comfortable teaching?

1. Mathematics
   (scale from a lot to a little)
2. Language
   (scale from a lot to a little)

3. Sciences
   (scale from a lot to a little)
4. Social sciences
   (scale from a lot to a little)
5. Computational thinking
   (scale from a lot to a little)

To finish, we will ask you 4 questions:

1. If you are running a race and you pass the person in second place, what place are you in?
2. A farmer had 15 sheep and all but 8 died, how many are left?
3. Maria's father has 3 daughters. The first two are named April and May, what is the name of the third daughter?
4. How many cubic meters of dirt are in a hole 3 meters deep x 3 meters wide x 3 meters long?

Thank you very much for your collaboration!

F.1.2. Endline Survey

Good morning:

As part of your participation in the Computational Thinking Narratives project developed by Ceibal with external researchers, we ask you to answer a few brief questions. The questionnaire takes no more than 10 minutes. Thank you very much for your collaboration!

To start, we will present a series of statements and you will have to answer how much you agree with them. We ask you to answer honestly. The scale goes from 1 to 5, where 1 is strongly disagree and 5 is strongly agree.

1. Girls and boys have a certain amount of intelligence and cannot do much to change it.
2. Girls have a certain amount of intelligence and cannot do much to change it.
3. Boys have a certain amount of intelligence and cannot do much to change it.
4. There are "good" or "bad" people in mathematics and not much can be done to change it. Some students are better at math and others not so much.
5. When girls and boys have to try hard in a school subject, it means they cannot be good at that subject.
6. When girls have to try hard in a school subject, it means they cannot be good at that subject.
7. When boys have to try hard in a school subject, it means they cannot be good at that subject.

Secondly, we will present a new series of statements for you to answer again how much you agree or disagree with them.

Many women with the same math grades as men have less interest in scientific and technological tracks in high school. Based on your experience, what are the main factors?

1. Lack of interest in science
2. Low inclination towards scientific subjects

3. Low self-esteem
4. Family encouragement towards other alternatives
5. Because they are influenced by gender stereotypes ("girls are bad at math")

Next, we will present an activity where you will have to respond as quickly as you can.

It is an activity composed of 4 rounds, where the first two rounds are for practice.

In the first round you will see girl and boy names and you will have to assign the word "girl" (located on the right of your screen) or "boy" (located on the left of your screen) as quickly as you can. To do this activity you must use the letter F on the keyboard to select "girl" and J to select "boy".

The instructions are clearly explained when you start the activity, but here is a preview of the interface you will see on your computer.

Now we will ask you to answer how much you agree or disagree with the following statements. The scale ranges from 1 to 5, with 1 being strongly disagree and 5 being strongly agree.

1. There are innate differences in math skills between men and women.
2. In general, men are better political leaders than women.
3. It is more important for men to go to university compared to women.
4. When jobs are scarce, men should have more right to work than women.

To finish, we will ask you some questions about your students:

1. What percentage of your students do you think struggle the most with math?
2. What percentage are boys?
3. What percentage of your students do you think struggle the most with language and writing?
4. What percentage are boys?
5. What percentage of your students do you think will go to University?
   (a) very low (0-25%)
   (b) medium (25-50%)
   (c) high (50-75%)
   (d) very high (75-100%)

F.2. Students

F.2.1. Baseline Survey

Hello!

We are curious scientists working at the Autonomous University of Barcelona in Spain and we want to know how to spark the interest of girls and boys like you. Can you help us understand what you like and how you think about some things?

You are very important to our study!

Today we are going to ask you to answer some questions. There are no right or wrong answers, you just have to check the option you like best, so we can know what you think about different things.

The activity is individual and it is very important that you do not look at what your classmate next to you is doing. If any question is confusing, raise your hand and we will help you. The activity is short and will not take more than 10 minutes.

We ask you to answer honestly as that will help a lot to improve our work. Remember that what you answer here is anonymous, neither your teacher nor anyone at the school will be able to know your answers.

Thank you very much for taking the time to answer it!

To start we will ask you some questions about the use of technology:

How much do you agree with the following phrases?

1. I am good at using computers
2. I am good at typing on the keyboard
3. I know how to use tablets or cell phones
4. It is easy for me to search for information on the Internet
5. Using a computer is important for learning
6. I like working in Scratch

Slider from Strongly disagree to Strongly agree (5 options)

Now we are going to propose two questions for you to decide according to your preferences:

1. Choose a number between 0 and 100. Everyone will choose a number, we will calculate the average with all the numbers, and divide it by 2. Your goal is to be as close as possible to the resulting value.
2. Imagine you have to decide how to distribute a prize between 2 people you do not know. What option do you prefer? (8,8); (10,9); (15,7); (16,2)

To finish, we are going to ask you some questions about yourself:

1. What gender do you identify with? (Female, Male, Other gender).
2. How old are you? Write with a number, please.
3. Who do you live with? You can check the options you need. (Mom, Dad, Brothers and/or sisters, grandfather and/or grandmother, uncles or aunts, other adult).
4. How many brothers/sisters do you have? If you don't have any, write 0.
5. Who is at your house when you arrive from school? You can check the options you need. (Mom, Dad, Brothers and/or sisters, grandfather and/or grandmother, uncles or aunts, other adult).
6. Thinking about your first reference person (check one box) (Mom, Dad, Brothers and/or sisters, grandfather and/or grandmother, uncles or aunts, other adult). Do they have a university degree? (Yes, No, I don't know)

7. Thinking about your second reference person (check one box) (Mom, Dad, Brothers and/or sisters, grandfather and/or grandmother, uncles or aunts, other adult). Do they have a university degree? (Yes, No, I don't know)
8. Thinking about your first reference person (check one box) (Mom, Dad, Brothers and/or sisters, grandfather and/or grandmother, uncles or aunts, other adult). What are they doing these days? (works all day, works half the day, is at my house, does not answer)
9. Thinking about your second reference person (check one box) (Mom, Dad, Brothers and/or sisters, grandfather and/or grandmother, uncles or aunts, other adult). What are they doing these days? (works all day, works half the day, is at my house, does not answer)
10. What would you like to be when you grow up? (Box for them to write the answer).

F.2.2. Endline Survey

Hello!

We're back! We are curious scientists working at the Autonomous University of Barcelona in Spain and we want to know how to spark the interest of girls and boys like you. Can you help us understand what you like and how you think about some things?

You are very important to our study!

Today we are going to ask you to answer some questions. There are no right or wrong answers, you just have to check the option you like best, so we can know what you think about different things.

The activity is individual and it is very important that you do not look at what your classmate next to you is doing. If any question is confusing, raise your hand and we will help you. The activity is short and will not take more than 20 minutes.

We ask you to answer honestly as that will help a lot to improve our work. Remember that what you answer here is anonymous, neither your teacher nor anyone at the school will be able to know your answers. It is important that you know that your answers are anonymous and neither your parents nor the teacher will be able to link your name to your answers.

Thank you very much for taking the time to answer it!

Let's start with the first part where we will give you 7 statements and we will ask you to answer how much you agree with these statements.

You must answer how much you agree or disagree with these statements. You will see 5 response options:

a. Strongly disagree
b. Disagree
c. Neither agree nor disagree
d. Agree
e. Strongly agree

Remember, there are no good or bad answers. You must select the option of your preference with the mouse. You will only be able to check one and no one will know your answer.

Great! Let's start with the first part. We will ask you to answer how much you agree with the following statements:

h. I have an amount of intelligence and I cannot do much to change it.
i. Girls have a certain amount of intelligence and cannot do much to change it.
j. Boys have a certain amount of intelligence and cannot do much to change it.
k. There are "good" or "bad" people at math and it cannot be changed.
l. When you have to try hard in a subject at school, it means you cannot be good at that subject.
m. When girls have to try hard in a subject at school, it means they cannot be good at that subject.
n. When boys have to try hard in a subject at school, it means they cannot be good at that subject.

Well done! In the next part, we will ask you who you think is better at doing things, girls or boys.

To do this, the answers you can give are the following:

a. Girls are more talented
b. Girls are a little more talented
c. Both are equally talented
d. Boys are a little more talented
e. Boys are more talented

Just like before, you must select the option of your preference with the mouse. There are no bad or good answers, be as honest as possible. If you don't understand, raise your hand and we will go help you.

Let's start!

Mathematics

a. Who is more talented?
b. Who has to work harder to get good results?
c. For whom will math be more important in their future job?

Language and writing

d. Who is more talented?
e. Who has to work harder to get good results?
f. For whom will language and writing be more important in their future job?

Now we want to know how your classmates think.

1. According to your classmates: Who is more talented in math?
2. According to your classmates: Who has to work harder to get good grades in math?

3. According to your classmates: For whom will math be more important in their future job?
4. According to your classmates: Who is more talented in language and writing?
5. According to your classmates: Who has to work harder to get good grades in language and writing?
6. According to your classmates: For whom will language and writing be more important in their future job?

Next, we will present an activity where you will have to respond as quickly as possible.

The activity instructions are explained on the next screen. Shall we review them?

It is an activity composed of 4 rounds, where the first two rounds are for you to practice.

In the first round you will see girl and boy names and you will have to assign the word "girl" (located on the right of your screen) or "boy" (located on the left of your screen) to each of those names.

To do this activity you must use the letter F on the keyboard to select "girl" and J to select "boy".

We show you an example: [SCREEN WITH AN EXAMPLE]

As you do the activity, you will see the instructions on the screen, if you do not understand, raise your hand and they will come to help you.

Remember to do it as fast as you can!

Now we will show you some statements about math and language and writing and you will have to answer according to your preferred option. You have 5 answer options:

a. No, not at all
b. Not much
c. A little
d. Rather yes
e. Yes, that is true.

Let's start!

Mathematics

a. I enjoy learning it
b. I wish I didn't have to study it
c. It is boring
d. I learn many interesting things
e. I like it
f. I like homework that has numbers
g. I look forward to classes
h. It is one of my favorite subjects

Language and writing

i. I enjoy learning it
j. I wish I didn't have to study it
k. It is boring
l. I learn many interesting things
m. I like it
n. I like doing homework that involves language and writing
o. I look forward to classes
p. It is one of my favorite subjects

Now, thinking about your first reference person (check one box)

a. Mother
b. Father
c. Sister
d. Brother
e. Grandmother
f. Grandfather
g. Guardian

Do you think they like math? Do you think they like language and writing?

Now, thinking about your second reference person (check one box)

a. Mother
b. Father
c. Sister
d. Brother
e. Grandmother
f. Grandfather
g. Guardian

Do you think they like math? Do you think they like language and writing?

Let's see what the next part looks like. In this section, I will briefly describe different professional areas. After each description, please answer three questions.

1. Are you interested?

2. Would you be good working in that profession?
3. Do you find that profession difficult?

You can answer following the same pattern as before:

a. No, not at all
b. Not much
c. A little
d. Rather yes
e. Yes, that is true.

You may not know all the words I am reading to you. It is not necessary that you understand everything perfectly. There are no bad or good answers. Simply respond according to your instinct. Let's start with the first description:

1. The first professional field is called 'engineering': Engineering professionals develop, design, calculate and improve technical installations, bridges, buildings or machines. Examples of professions in this field include civil engineers and mechanical engineers.
    a. Are you interested?
    b. Would you be good at that profession?
    c. Do you find that profession difficult?
2. The second professional field is called 'social work': Social work involves supporting and advising individuals, families and groups when they have social problems, for example, in disputes and difficult situations. Examples of professions in this field include social workers and assistants.
    a. Are you interested?
    b. Would you be good at that profession?
    c. Do you find that profession difficult?
3. The third professional field is called 'computing and programming': Programming means inventing and testing programs on the computer. Computer professionals also help with computer-related problems. Examples of professions in this field are software developer or web page designer.
    a. Are you interested?
    b. Would you be good at that profession?
    c. Do you find that profession difficult?
4. The fourth professional field is called 'language and culture': Language and culture involve translating from one language to another, writing newspaper articles, books or plays, organizing events like concerts or working in a museum. Examples of professions in this field are journalist or translator.
    a. Are you interested?
    b. Would you be good at that profession?
    c. Do you find that profession difficult?

5. The fifth occupational field is called 'mathematics': Mathematics professionals are dedicated to exploring and applying mathematical principles, from optimizing algorithms to simulating industrial processes, to solve a variety of problems and challenges in various fields. Examples of professions in this field are mathematicians or math teachers.
    a. Are you interested?
    b. Would you be good at that profession?
    c. Do you find that profession difficult?
6. The sixth professional field is called 'Art and design': Art and design involve creating works of art, inventing new furniture, designing new houses and performing on stage. Examples of professions in this field are artists and designers.
    a. Are you interested?
    b. Would you be good at that profession?
    c. Do you find that profession difficult?