



Increasing perseverance in math: Evidence from a field experiment in Norway[☆]

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ABSTRACT

Research by psychologists and economists demonstrates that many non-cognitive skills are malleable in both children and adolescents, but we have limited knowledge on what schools can do to foster these skills. In a field experiment requiring real effort, we investigate how schools can increase students' perseverance in math by shaping students' beliefs in their abilities to learn, a concept referred to by psychologists as "mindset." Using protocols adapted from psychology, we experimentally manipulate students' beliefs in their ability to learn. Three weeks after our treatment, we find persistent treatment effects on students' perseverance and academic performance in math. When investigating subsamples, we find that students, who prior to the experiment had less of a belief in their ability to learn, generate the treatment effect. The findings suggest that a low-cost intervention focused on students' mindset can improve students' engagement and performance.

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1. Introduction

Non-cognitive skills, such as self-control and perseverance, predict success in education and in labor markets (Borghans et al., 2008; Heckman et al., 2006; Roberts et al., 2007). While researchers are still trying to understand the causal mechanisms, there is strong evidence that individuals with higher non-cognitive skills are more likely to graduate from high school, have higher rates of college attendance and completion, higher wages and better employment, and even better health outcomes (Carneiro et al., 2007; Kautz et al., 2014). Moreover, research by psychologists and economists demonstrates that many non-cognitive skills are malleable (Alan et al., 2016; Durlak et al., 2011; Kautz et al., 2014). Still, however, we have limited knowledge on what schools can do to foster these skills.

While non-cognitive skills may be acquired through motivation or self-regulation programs relying on direct instruction and repetitive practice, meta-analyses find that this approach has mixed results. It works reasonably well with young children,

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but shows weak or null effects with adolescents (Durlak et al., 2011; Heckman and Kautz, 2013; Yeager et al., in press). An alternative approach to developing non-cognitive skills, tested here, focuses on students' beliefs. Rather than thinking of perseverance as a fixed ability, we think of perseverance as a series of repeated choices. We define a student with high perseverance as someone who consistently chooses to exert high effort – she stays focused on challenging tasks, works hard, and does not give up. As a choice, perseverance should be sensitive to beliefs about the payoff of effort. Therefore, changing beliefs about effort – in a way that lasts over time – might result in changes in perseverance even after a relatively minimal belief-change intervention.

An extensive literature in psychology and labor economics has demonstrated that students' beliefs, such as self-efficacy, locus of control or grit, predict their perseverance and choices (Alan and Ertac, 2015; Bandura, 1977; Cobb-Clark, 2015; Cobb-Clark and Schurer, 2013; Coleman and DeLeire, 2003; Duckworth et al., 2007; Duckworth and Seligman, 2005). Although informative, this research is correlational. Our identification strategy is to randomly assign students to a well-validated psychological intervention that is known to change beliefs about effort: a *growth mindset* intervention (Dweck 2006; Yeager and Dweck 2012), also referred to as an “incremental theory of intelligence” intervention (Dweck and Leggett, 1988). Growth mindset interventions shape students' beliefs in their ability to learn, and cause lasting improvements in school outcomes (Aronson et al., 2002; Blackwell et al., 2007; Good et al., 2003; Paunesku et al., 2015; Yeager et al., 2016). In the interventions students learn about the brain's potential to grow and change through dedication, hard work on challenging tasks, finding the right learning strategies, and seeking assistance from others. The growth mindset intervention is designed to counteract the “fixed mindset,” which is the belief that intelligence or talents are fixed traits. By contrast, students with a “growth mindset” believe that their abilities can be developed.

In a field experiment requiring real effort, we investigate how schools can increase students' perseverance in math by shaping students' beliefs in their abilities to learn or in their potential to benefit from effort. We rely on the web-based mindset intervention in Yeager et al. (2016), which was based on prior work by Aronson et al. (2002) and Paunesku et al. (2015). We adapted the intervention to the Norwegian language, culture and context. The treatment condition exposes students to growth mindset through online reading and writing exercises. These exercises focus on (1) how intellectual abilities are malleable and accordingly how the brain can grow and change; (2) how hard work on challenging exercises improves the neural connections in one's brain; (3) how growth mindset aids in coping with confusion and difficulty; and (4) how growth mindset can be used to strive toward personal goals, giving more purpose to exert effort in difficult tasks (Yeager et al., 2014). The control condition has analogous activities, which teach students facts about memory and brain functioning, but does not address the malleability of intellectual ability.

In the spring of 2016, 385 Norwegian high school students participated in the field experiment. During normal school instructional time, we introduced students to a website. Each student logged in individually to the website on personal laptops. Once students logged in, our software randomly assigned them to either the mindset or control conditions. The students worked on the online reading and writing exercises during two sessions of 45 min, two weeks apart. In the third session, we gave students a real effort task, designed to capture a familiar school activity, in which perseverance is critical to learn and succeed. Specifically, students received a series of 34 multiple-choice algebra questions sequentially. The algebra questions were challenging, possibly making many students frustrated and tempted to give up. We told the students that we would like them to “do their best” and that they “may learn something from working on the math questions.” We also explained carefully that students' answers would be kept confidential and that their performance would not affect their grade. As many students did not have time to finish all the questions, or “gave up” – clicking fast through the questions – we look at how many correct answers students had on the first 10, 20 and all 34 questions.

The experimental results demonstrate that treated students have significantly more correct answers on the first 10 questions compared to students in the control group (19 percent of the standard deviation), but there is no significant difference between treated and control when looking at the first 20 or all 34 questions. Subsample analysis demonstrates that the treatment effect is entirely driven by students who initially had a fixed mindset. For student who entered the experiment with a pre-existing fixed mindset, the treatment effect is large and significant for all three outcome measures; treated students scored 35, 34 and 29 percent of a standard deviation higher than control students on the first 10, 20 and all 34 questions, respectively. For students who already had a growth mindset pre-treatment, there are no significant treatment effects. Our descriptive statistics demonstrate that prior to the experiment, students with low grade point average (GPA) and students in vocational tracks have less of a growth mindset. Investigating these subsamples we find large and significant treatment effects. Among students in vocational tracks, the treatment increased the score on all 34 questions by 25 percent of a standard deviation. Our results are consistent with the hypothesis that it is possible to increase students' perseverance in math by shaping their beliefs in their abilities to learn, in particular among students who initially had a fixed mindset.

This paper relates to several strands of literature in economics. First, as noted above, our work builds on the emerging literature on non-cognitive skills by investigating whether schools can foster students' perseverance by shaping their beliefs in their abilities to learn. This is important because the study offers an identification strategy for testing the effect of non-cognitive skills on life outcomes. Second, our work also relates to recent developments in behavioral economics of education (Koch et al., 2015; Lavecchia et al., 2014) which attempt to understand how low-cost behavioral or psychological interventions can help students better utilize the learning opportunities already within the educational system (e.g. Bettinger et al., 2012; Carrell et al., 2016; Castleman and Page, 2015). We contribute to this literature by investigating how a brief, low-cost psychological intervention can lead students to increase their effort in a learning task three weeks later. Third, our mindset experiment builds on other behavioral economics experiments designed to understand individual's motivation and

performance in real effort choices in the lab or field (Azmat and Iriberry, 2010; Bradler et al., 2016; Eriksson et al., 2009; Koch et al., 2015; Kvaløy et al., 2015).

Finally, our experiment contributes to the psychological literature on mindset. The psychological mechanisms for mindset effects are clearly defined and strongly illustrated in laboratory experiments: growth mindset interventions change students' effort beliefs, their attributions, and their goals (Burnette et al., 2013). Yet as argued by Wilson and Buttrick (2016) and Miller et al. (2017), the behavioral mechanisms that explain how a change in beliefs can translate into a change in grades months or years later, are not fully documented. This makes “long lag” intervention effects seem “magical” (Yeager and Walton, 2011). We shine some light into this behavioral “black box”, by demonstrating that the mindset intervention affects perseverance in a real effort learning task which took place three weeks after the intervention. While our study focuses on mindset, it builds upon the extant literature demonstrating that behavioral training can influence academic outcomes (e.g. Alan et al., 2016; Duckworth and Seligman, 2005; Durlak et al., 2011).

2. Background

2.1. Sample and institutional context

The participants in our experiment are Norwegian first year high school students in Rogaland County. We focus on Norway for three distinct reasons. First, to date, the existing research on mindset focuses on the United States. Using a sample outside the United States can advance understanding of mindset. The capability of the Norwegian government to track students throughout their lifetime, gives the possibility to measure the long-run impacts of growth mindsets. Second, Norway, like many countries, divides high school students into vocational and academic tracks. This tracking is often correlated with prior achievement, and as we show below, the vocational students in our sample have significantly lower incidence of growth mindsets. Third, our sample is also drawn out of convenience. Multiple coauthors live in the Rogaland region of Norway and have existing partnerships in implementing educational interventions. At the time of the research, educational policymakers throughout Norway were discussing the academic research on growth mindset and its implications for Norway.

In Norway, students start high school around age 16 after ten years of compulsory schooling similar for everybody (primary and middle school).¹ A student can apply to any high school in her county. When applying a student has to decide whether to enroll in a vocational track, which leads directly to employment, or an academic track, which prepares students to attend college after high school completion. Students rank three desired choices, and acceptance is based on students' GPA from middle school. All students are guaranteed acceptance into a high school in the county.

Norwegian high school typically last three to four years depending on the specific program. Only 70 percent of students complete high school within five years. For vocational track students, completion rates are particularly low – only 55 percent complete within five years. While Norwegian policymakers have aimed several reforms at improving high school completion rates, there have been no systematic efforts to alter students' beliefs in their abilities to learn as a means of improving educational outcomes.

2.2. Conceptual framework

We define a student with high perseverance as someone who consistently exerts high effort – she stays focused on task, works hard on challenging yet potentially rewarding tasks, and does not give up. Below we present a stylized model illustrating how shaping students' beliefs in their abilities to learn can affect their perseverance.

Consider a learning situation. A student chooses how much effort to exert. By staying focused on task, working hard and not giving up, the student can benefit from learning. However, there may be an opportunity cost of exerting high effort – for example, the student cannot check her phone, day dream, or talk to a class mate.

Let $pB(e)$ represent the student's expected benefit of learning when exerting effort, e , where $B' > 0$, $B'' < 0$ and p is the student's belief in her abilities to learn, i.e. how effort translate into benefit of learning. Let $C(e)$ represent the opportunity cost of exerting effort, where $C' > 0$ and $C'' > 0$. A utility maximizing student chooses effort level e^* such that $C'(e^*) = p \cdot B'(e^*)$. From this first order condition, it follows that $\frac{de^*}{dp} > 0$ and $\frac{d^2e^*}{d^2p} < 0$. Thus, we have the following two conjectures:

Conjecture 1. It is possible to increase a student's effort by increasing her belief in her ability to learn.

Conjecture 2. The effort-effect of increasing the student's belief in her abilities to learn is higher, the lower the student's initial belief.

2.3. Academic mindset interventions

In psychology, a student's belief in her abilities to learn is referred to as her academic mindset (Dweck, 2006). Students with a “fixed mindset” believe their intelligence or talents are fixed traits. Studies using survey measures of mindsets and

¹ About 9 percent of students in our sample were older than 16, meaning that they either delayed kindergarten entry, experienced grade repetition at some point in their academic career, or “took time off” after compulsory schooling.

	Pre intervention measures	Intervention	Post intervention measures
Session 1	- Baseline Mindset Measures	-Treated: Mindset -Control: Placebo	
Session 2		-Treated: Mindset -Control: Placebo	- Mindset Measures - Make a Math Worksheet
Session 3			- Solve Math Worksheet - Real Effort Task

Fig. 1. Content of Computer Program.

experimental manipulations of mindsets in laboratory and school settings suggest that a fixed mindset shapes students' academic achievements in many ways (Dweck 2006; Yeager and Dweck 2012; Yeager and Walton, 2011). First, students with a fixed mindset avoid academic challenges. They want easier problems that will make them look and feel smart (Mueller and Dweck 1998; Yeager et al., 2016). Second, a fixed mindset leads to unproductive beliefs about efforts. For example, a student with a fixed mindset might say "If I have to try hard at math, I'm not smart at math" (Blackwell et al., 2007). Last, fixed-mindset students are less resilient. Instead, they hide setbacks and deficiencies, not wanting people to see them as having low ability. They fail to ask for help and sometimes even lie about low scores (Mueller and Dweck, 1998).

By contrast, students with "growth mindsets" believe that intelligence can grow and improve in response to effort, good strategies, and help from others. From this perspective, an academic challenge is not a threat to one's ability; it is an opportunity for learning and improvement. In a growth mindset, effort is a good thing: a student might say "trying harder makes you smarter" (Blackwell et al., 2007). In the face of a difficult problem, a growth mindset student is more resilient, seeks appropriate help, or switches strategies. The student does not hide confusion. Compared to a fixed mindset, holding a growth mindset predicts more learning, better learning strategies, and higher grades over time, provided that the schoolwork is challenging (Blackwell et al., 2007; Yeager and Dweck 2012).

There is substantial evidence suggesting that parents and teachers socialize children's mindsets through everyday communication (Kamins and Dweck 1999; Mueller and Dweck 1998; Rattan et al., 2015). Subtle verbal feedback from adults can put children in a fixed mindset and undermine internal motivation. This can happen even from valued caregivers trying to encourage children. For example, a classic paper by Mueller and Dweck (1998) showed that praising young adolescents for their intelligence – telling them they were "smart" when they did well – created a fixed mindset and undermined their resilience in the face of later struggle. In contrast, praising students' "processes" (efforts or strategies) put children in a growth mindset and fostered resilience.

Recently several studies have demonstrated that precise theory-based interventions can communicate a growth mindset to youths and produce lasting improvements in students' grades (Aronson et al., 2002; Blackwell et al., 2007; Good et al., 2003; Paunesku et al., 2015; Yeager et al., 2016). These interventions appeal to neuroscience and evidence on the malleability of the brain. To communicate the malleability of intelligence, these interventions use physical exercise as a metaphor for growth mindset. The interventions teach the students to think of their brains as muscles, which get stronger as one exercises them. The intervention depicts new neuronal connections growing as students complete challenging math problems.

3. Experimental design

3.1. Intervention and measures

We develop a computer program with three online sessions, each lasting about 45 min. We base content and visual layout in Sessions 1 and 2 on the intervention in Yeager et al. (2016) (also see Paunesku et al., 2015). However, by the means of a professional translator and interviews with several focus groups of Norwegian high school students, we carefully adapted the material to the Norwegian language, culture and context. Session 3 consists of a real effort task in which the students have to solve a series of algebra questions. Fig. 1 illustrates the content of the three sessions.

In Session 1 students first answer survey questions designed to measure students' mindsets at baseline.² In particular, we ask how much, on a scale from 1 to 6, the student disagrees (1) or agrees (6) with the following statements (assigned variable name in parenthesis):

² Below, we only list survey questions used for this paper. The students received other survey items, designed to answer different research questions. All survey questions were identical for treated and control.

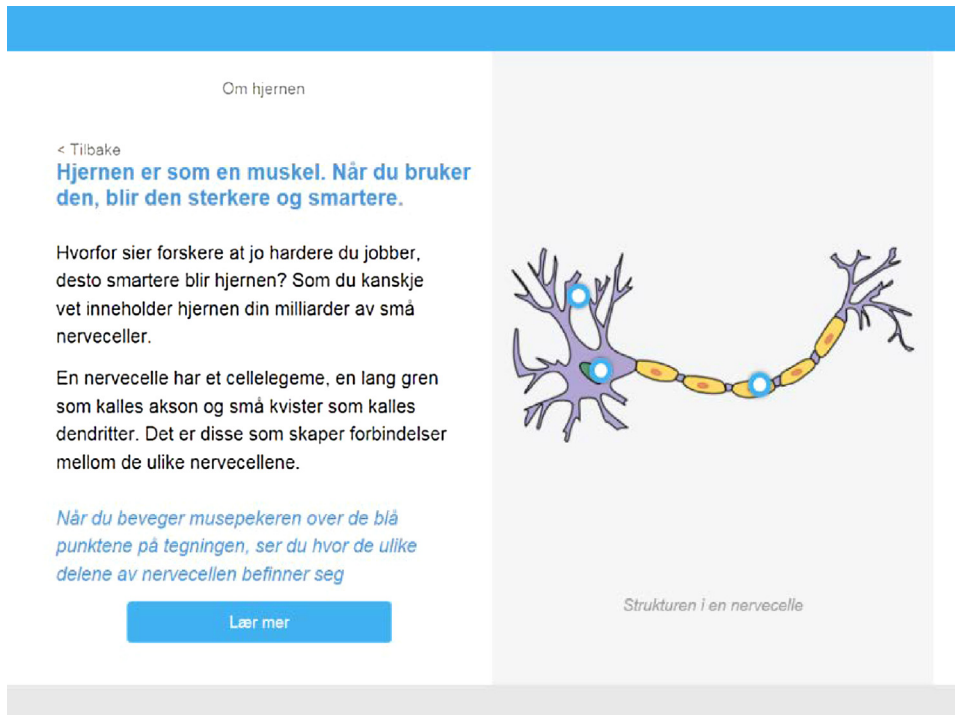


Fig. 2. Screen Shot from Computer Program.

- “You have a certain amount of intelligence, and you really can’t do much to change it” (Fixed Mindset 1);
- “Your intelligence is something about you that you can’t change very much” (Fixed Mindset 2);
- “Being a ‘math person’ or not is something that you really can’t change. Some people are good at math and other people aren’t” (Fixed Mindset Math); and
- “When you have to try really hard in a subject in school, it means you can’t be good at that subject” (Fixed Mindset Effort).

These mindset measures have been used and validated in numerous studies, demonstrating that they strongly predict grades and performance on behavioral tasks (see e.g. Burnette et al., 2013; Yeager et al., 2016)

After responding to the survey questions, the students receive the intervention. The computer program randomly allocates students to either the treatment or control conditions. The treated students have to do three cognitive exercises. First, students have to read an article about research in neuroscience that demonstrates the brain’s potential to grow and change, originally written for the experiment in Blackwell et al. (2007) and substantially revised in Yeager et al. (2016). The article presentation runs over several screens (one of which appears in a single screenshot in Fig. 2) and has a stylized visual layout with illustrations. It also uses the metaphor that the brain is like a muscle that grows in response to challenging learning experiences. Second, students are asked to summarize the article and explain how its message relates to their own lives. Linking information to the self in this way makes it more self-relevant and easier to recall (Bower and Gilligan, 1979; Hulleman and Harackiewicz, 2009). Third, students are asked what growth mindset advice they might give to a friend who was struggling in school. Providing advice to others is a “saying-is-believing” tactic to encourage students to internalize the ideas by endorsing them to someone else (see e.g. Aronson et al., 2002).

Students in the control condition, like those in the treatment condition, read a brief article about the brain and answer reflective questions. However, they do not learn about the brain’s malleability. Instead, they learn about basic brain functions and their localization, for example, the key functions associated with each cortical lobe. The experimental conditions are designed to look very similar to discourage students from comparing their materials. It involves the same type of graphic art – e.g. images of the brain, animations – as well as compelling stories.

In Session 2, the intervention uses insights from the social psychology of attitude change and persuasion, what we call “supportive psychologies”, to allow a brief, online intervention to achieve lasting effects. The purpose of the “supportive psychologies” is to create a gestalt impression that the growth mindset message is *memorable, credible, normal, and important*. Specifically, Session 2 repeats the metaphor from Session 1, that the brain is like a muscle that grows in response to challenging tasks (*memorable*); It includes quotes from scientists and celebrities who endorsed the notion that the brain develops when it learns and explained how a stronger brain could lead to improvements in personal and social welfare (*credible*); It leverages social norms by including quotations from past participants endorsing the program messages (Cialdini and Goldstein, 2004) (*normal*); Finally, Session 2 emphasizes a purpose for learning (Yeager et al., 2014) by including prosocial

beyond-the-self motives for adopting and using a growth mindset (Grant 2013; Yeager et al., 2016) (*important*). For example, one screen in the intervention reads as follows: “People tell us that they are excited to learn about a growth mindset because it helps them achieve the goals that matter to them and to people they care about. They use the mindset to learn in school so they can give back to the community and make a difference in the world later.”

In addition to reinforcing the brief mindset intervention, the “supportive psychologies” are important for the following reason: This study is one of the first papers in economics focusing on mindset. One of our goals is to replicate mindset as true to the original psychology literature as possible. Some prior work by economists (e.g. Dee 2014) has failed to replicate psychological interventions possibly in part because of substantial deviations from the psychological intervention. We are relying on the exact script (adapted to Norwegian language and context) of the largest and most effective mindset study to date.

The “supportive psychologies” do present some issues in the interpretation of the results. In particular, our intervention in Session 2 could affect academic performance through social pressure: The use of credible role models and social norms may create social pressure for students to adopt growth mindsets. We are unable to disentangle whether the impacts derive primarily from education about the mind (Session 1) or from the social pressure exerted in Session 2. Both sessions point students toward improving growth mindset, but we do not identify the relative strength of the effect from the two sessions.

Similar to Session 1, the control students’ activity in Session 2 is designed to be parallel to the treatment activity. Students learn more about the brain, but not about its malleability and growth mindset. In general, we took every precaution to make sure that there was minimal to no contamination across treatment categories during implementation. If some contamination occurred after implementation (for example if students talked to each other about treatment material), this is likely to bias our estimated impacts downward.

After the intervention material, Session 2 provides all the students with the same series of survey questions, measuring students’ mindsets, as at the start of Session 1. Thereafter we include a measure of challenge seeking which prior research has associated with growth mindsets (Blackwell et al., 2007; Mueller and Dweck 1998). Similar to Yeager et al. (2016) we let students create their own math worksheet which they will have to work on in Session 3. Students can pick from easy questions from which they likely will not learn new skills, or hard questions, which may require more effort but provide more learning opportunities. As measures of students’ challenge seeking, we use number of very hard questions selected and number of very hard or somewhat hard questions selected. The questions were provided by The Norwegian Directorate for Education and Training, and we categorized them into easy, hard and very hard based on previous students’ scores on each question.

Finally, in Session 3 students first have to solve two randomly drawn questions from the worksheet they created in Session 2.³ After the worksheet questions, the students have to participate in a real effort task, consisting of 34 multiple choice algebra questions, given sequentially.⁴ The algebra questions were challenging, and several students did not have time to work on all the questions. On average, the students answered correctly 45, 41, and 37 percent of the first 10, 20 and 34 questions, respectively.

The on-screen introduction to the algebra questions tells the students that they will be given a series of algebra questions, and that they should try to do their best to find the correct answer. Moreover, it explains that students might learn something from working on the math questions, but that their performance will not affect their grade. As many students gave up or ran out of time on the last questions, we use number of correct questions on the first 10, 20, and all 34 questions as measures of students’ effort on the algebra questions.

Notably, the students did not know that they would receive algebra questions in Session 3, so there was no way to prepare. Moreover, algebra was not on the curriculum in school between Session 1 and Session 3. Thus, if we find a treatment effect on these measures, it is reasonable to interpret it as an effect of effort (students are more focused on task, work harder and do not give up) and *not* that treated students have actually become better in algebra (although we can not rule out that some students may have been sufficiently motivated to pursue outside learning experience).

A possible concern with our real effort task is demand induced effects, that students in the experimental condition increase effort to comply with the experimenters’ wishes, and not because they have more of a growth mindset. To limit this possibility, we provide no prompts before presenting the test questions in Session 3, and the format of the session has minimal reminders of the prior sessions: Experimenters were not present in the classroom, and the graphics on the test questions did not reiterate the experiment. Furthermore, effects caused by a change in mindset are expected to differ across subsamples (see Hypothesis 2 below), whereas there are no clear reason to expect differential demand induced effects.

As a secondary matter, our data also allow us to investigate time spent on each algebra question. On the one hand, we could imagine that students with more perseverance manage to stay more focused and work harder and hence are able to move faster through the problems. On the other hand, given the difficulty of the questions, students with more perseverance may have spent more time trying to solve a question before giving up. They may have elected to try different approaches

³ We did not use this data, as selection in Session 2 (treatment affects challenge seeking) may affect performance on these questions. However, giving the students time in Session 3, to work on some questions from the worksheet, is still an important part of the design to avoid deception in Session 2.

⁴ The first 13 questions were the same for all students. Thereafter, the computer program randomly assigned the students to one of three groups, and each group received the remaining algebra questions in different order. The questions were selected from the publicly released NAEP test questions and the California Standards Tests questions.

instead of making a random guess and moving on to the next question. As such, we do not have a clear hypothesis, as to how our intervention affected time use. When investigating time spent on the first 10, 20 or 32 min (results available from authors on request), we find no significant treatment effects neither on the full sample nor on relevant subsamples.

3.2. Hypotheses

Recall from the stylized model in Section 2.2, if the treatment increases a student's belief in her abilities to learn, this increases her marginal benefit of effort, and leads to an increase in the optimal effort level in a learning situation (Conjecture 1). As such, we hypothesize:

Hypothesis 1. The treatment has a positive effect on a student's effort in the real effort task in Session 3.

The stylized model also demonstrated that an increase in a student's belief in her abilities to learn, increases optimal effort level at a diminishing rate (Conjecture 2). As such, we hypothesize:

Hypothesis 2. Treatment effects on effort in the real effort task are larger for students who initially have low beliefs in their abilities to learn.

Hypothesis 2 is also consistent with several studies demonstrating that initially low performing students benefit more from mindset interventions, and that a fixed mindset is more common among these students prior to the intervention (Paunesku et al., 2015; Yeager et al., 2016).

4. Sample and procedures

In the spring of 2016, all first year students at a public high school in rural Norway participated in the field experiment. As the school serves a large region, it is large and offers both a vocational and academic track. Participation was mandatory as part of the school instruction, but students had to consent to participate in the research project. When the student logged on to the first session, they received information about the research project and had to make their consent decision. We had 458 students participate in the first session, among whom 385 students consented to participate in the research project.

After a student had made the consent decision, we randomly assigned the student to either the mindset (treatment) or control condition. Among the students who consented, 22 students had missing registry data on middle school grades. Another 9 students were older than 20 years old.⁵ Dropping these students from our sample resulted in a Session 1 sample of 354 students. Absence is a major concern in Norwegian high schools, and we experienced some attrition in Sessions 2 and 3. From our Session 1 sample, 289 and 254 students participated in Sessions 2 and 3, respectively. Our balance test (see Table 1) demonstrates that attrition was not significantly correlated with treatment status. Notably, we collected data for students in Session 3 even if they had not participated in Session 2, i.e. received the treatment reinforcement.

We implemented all sessions in the students' classroom during school hours. The students used their own laptop computers and headset.⁶ At the beginning of each session, we read a brief script to all the students. We told the students that they were about to log onto a computer program designed to learn about the brain and reflect on learning. We asked the students to work independently and not talk to other students. We also emphasized that students should do their best and that their answers would be kept anonymous and not affect their grades. We assured them that their teacher or school would never see their individual answers. Finally, we told the students that the session would last for 45 min and provided them with logon information. In Session 1 and Session 2, members of our research team administered the protocol with the teacher present in the classroom. In Session 3, the teachers were responsible for implementation. We provided a script to them. Members of our research team were still present at the school in case the teachers had any questions or technical challenges. In all three sessions, if students finished prior to the 45 min, they were asked to work on other schoolwork. There are four open-ended questions in treated Session 1. The frequency of students putting effort into the open-ended questions suggest that most students paid attention to the treatment material. About 85 percent answered substantively, which was defined as any attempt of a sincere answer.

Students logged on with a unique student number and password assigned to each student by the school district administration. Teachers were unaware of students' treatment status. For the students who consented, the school district provided us with registry data utilizing the same unique student number. The school district de-identified the data before they provided the data to our team. From the registry data, we employ the following variables: GPA and math grade⁷ from middle school,

⁵ This implies lagging behind regular school progression by at least four years.

⁶ A laptop is mandatory for schoolwork. All the students have school district subsidized laptops. We had some extra headsets to lend to students who did not have headset.

⁷ Six students were registered without a math grade. These missing observations were replaced by predicted values (prediction based on baseline mindset measures, GPA, gender and vocational track). The correlation between predicted and observed values are 0.72. Results are robust with and without these students.

Table 1
Descriptive Statistics and Balance Test.

	Session 1			Session 2			Session 3		
	Control	Treatment	Difference	Control	Treatment	Difference	Control	Treatment	Difference
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
GPA	0.083 (0.916)	-0.081 (1.072)	-0.165 (0.106)	0.165 (0.809)	0.092 (0.899)	-0.072 (0.101)	0.224 (0.892)	0.141 (1.029)	-0.083 (0.121)
Math grade	0.066 (0.970)	-0.064 (1.026)	-0.130 (0.106)	0.130 (0.940)	0.062 (1.005)	-0.067 (0.115)	0.172 (0.956)	0.141 (1.029)	-0.031 (0.125)
Vocational track	0.583 (0.494)	0.664 (0.473)	0.082 (0.051)	0.566 (0.497)	0.645 (0.479)	0.080 (0.057)	0.489 (0.501)	0.561 (0.498)	0.073 (0.063)
Female	0.440 (0.497)	0.525 (0.500)	0.085 (0.053)	0.441 (0.498)	0.548 (0.499)	0.107* (0.059)	0.511 (0.511)	0.595 (0.492)	0.084 (0.062)
Older than 16	0.091 (0.289)	0.078 (0.269)	-0.013 (0.030)	0.055 (0.304)	0.027 (0.164)	-0.027 (-0.023)	0.075 (0.265)	0.057 (0.234)	-0.017 (0.031)
Fixed Mindset 1	0.049 (0.996)	-0.047 (1.004)	-0.096 (0.106)	0.008 (0.977)	-0.062 (.983)	-0.071 (0.115)	0.036 (0.988)	-0.108 (0.993)	-0.144 (0.124)
Fixed Mindset 2	0.041 (0.993)	-0.040 (1.008)	-0.081 (0.106)	0.046 (0.988)	-0.050 (0.988)	-0.097 (0.116)	0.027 (0.957)	-0.047 (0.979)	-0.074 (0.121)
Fixed Mindset Math	0.047 (1.013)	-0.045 (0.987)	-0.092 (0.106)	0.040 (0.974)	-0.109 (0.968)	-0.150 (0.114)	0.029 (0.968)	-0.034 (0.951)	-0.063 (0.120)
Fixed Mindset Effort	-0.035 (0.965)	0.034 (1.034)	0.070 (0.106)	-0.111 (0.885)	0.000 (0.987)	0.112 (0.110)	-0.090 (0.906)	0.044 (1.004)	0.135 (0.121)
Baseline Growth Mindset	-0.038 (1.020)	0.036 (0.982)	0.075 (0.106)	0.001 (0.968)	0.079 (0.936)	0.078 (0.112)	-0.005 (0.984)	0.054 (0.957)	0.059 (0.122)
N	175	179	354	145	144	289	133	121	254

Notes: For each session sample, columns provide the mean (and standard deviation) for the control group and the treated group, and the estimated coefficient (robust standard error) from regressing each covariate against treatment status. * $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

Table 2
Correlation between Pre-Treatment Mindset Measures.

	Fixed Mindset 1	Fixed Mindset 2	Fixed Math Mindset	Fixed Effort Mindset
Fixed Mindset 2	0.690**			
Fixed Math Mindset	0.281**	0.425**		
Fixed Effort Mindset	0.212**	0.322**	0.299**	
Baseline Growth Mindset	-0.765**	-0.845**	-0.696**	-0.600**

Notes: * $p < 0.10$, * $p < 0.05$, ** $p < 0.01$. Session 1 sample ($n = 354$).

high school track (indicator for vocational), gender (indicator for female) and age (indicator for lagging behind regular school progression, i.e. being older than 16 years).

5. Results

5.1. Balance test and descriptive statistics

Table 1 presents our descriptive statistics and balance tests. The four Fixed Mindset measures corresponds to the four survey questions as reported in Section 3.1. These variables are standardized with mean zero and standard deviation one using the Session 1 sample, and a positive score indicates a fixed mindset. The *Baseline Growth Mindset* measure is the mean of the four fixed mindset metrics, where the scale is reversed and standardized. Hence, a positive score indicates a growth mindset. For the ease of interpretation, we have also standardized GPA and math grade from middle school using the Session 1 sample. *Older than 16* is an indicator for lagging behind regular school progression. The columns labeled Control and Treatment provide summary statistics for the control and treatment group in each session. In the Session 1 control group, we can see that about 44 percent of the students are female; 58 percent are in the vocational track; and 9.1 percent of students are one or two years older than the on-track age of 16. All other covariates are standardized. When comparing across sessions, the numbers indicate that the probability of completing all sessions are somewhat higher for those with a high GPA, being on academic track, females, and having a pre-intervention growth mindset. We regress each covariate against treatment status, and present the resulting coefficient and robust standard error in columns labeled Difference. We find that there are significantly more females in the treated group in Session 2 ($p < 0.1$), but all other characteristics are well balanced across treatment status. We conclude that randomization was successful and that attrition in Sessions 2 and 3 did not lead to significant differences in treatment status.

Table 3
Predictors of Baseline Growth Mindset.

	(1)	(2)	(3)	(4)	(5)	(6)
GPA	0.250** (0.052)					0.139* (0.077)
Math grade		0.260** (0.051)				0.179* (0.075)
Vocational track			−0.282* (0.109)			0.053 (0.129)
Female				0.151 (0.106)		0.082 (0.105)
Older than 16					−0.157 (0.191)	0.107 (0.193)
R-squared	0.060	0.065	0.016	0.003	0.003	0.066

Notes: † p < 0.10, * p < 0.05, ** p < 0.01. Dependent variable: Baseline Growth Mindset. Each column presents a separate regression and reports the estimated coefficient (robust standard error) for all included covariates. Session 1 sample (n = 354).

Table 4
Treatment Effect on Post-Treatment Mindset and Challenge Seeking in Session 2.

	Post-Treatment Growth Mindset		Choosing “Very Hard” Challenge Questions		Choosing “Hard” or “Very Hard” Challenge Questions	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.557** (0.113)	0.545** (0.090)	0.234* (0.117)	0.285** (0.110)	0.240** (0.117)	0.300** (0.111)
GPA		0.055 (0.085)		0.040 (0.105)		0.119 (0.105)
Math grade		0.228** (0.068)		0.378** (0.084)		0.407** (0.084)
Vocational track		0.006 (0.114)		0.159 (0.140)		−0.006 (0.140)
Female		0.002 (0.092)		−0.468** (0.113)		−0.417** (0.114)
Older than 16		0.323 (0.225)		−0.204 (0.277)		−0.094 (0.277)
Baseline Growth Mindset		0.522** (0.048)		0.045 (0.059)		0.020 (0.059)
R-squared	0.075	0.435	0.010	0.144	0.011	0.141

Notes: † p < 0.10, * p < 0.05, ** p < 0.01. First row lists the dependent variable. Each column presents a separate regression and reports the estimated coefficient (robust standard error) for all included covariates. Session 2 sample (n = 289). For columns (1) and (2): n = 288.

In Table 2 we present a correlation matrix of our mindset measures presented in Section 3.1. *Fixed Mindset 1*⁸ and *Fixed Mindset 2* represent two different wordings of the same question, and it should not be surprising that they are highly correlated. We can also see that these direct measures of a fixed mindset are strongly correlated with our measures of having a fixed mindset when it comes to Math (*Fixed Mindset Math*) and Effort (*Fixed Mindset Effort*). These are more indirect measures which measure the consequences of having less of a growth mindset. Throughout we will use *Baseline Growth* as our preferred mindset measure.

In Table 3 we investigate how our pre-treatment covariates predicts a growth mindset. We can see in Columns 1–3 that the presence of growth mindset seems to be significantly more likely for students with high GPA/math grade and for students who do not attend vocational tracks. Vocational tracks in Norway generally include students with lower academic credentials. In Column 5 we add all predictors to the same model and we find that there is only a significant relationship between GPA/math grade and growth mindset.

5.2. Treatment effects

In Table 4 we investigate treatment effects on outcome measures gathered at the end of Session 2. First, we see if the treatment affected the measure of growth mindset. We gathered the same measures of mindset post-treatment as we did at baseline. *Post-Treatment Growth Mindset* is then constructed identically to our *Baseline Growth Mindset* variable, and standardized on the Session 2 sample. We can see from Column 1 that there is a large and significant effect of treatment on

⁸ One student did not respond to the first fixed mindset question. This missing observation was replaced by the predicted value (prediction based on baseline mindset measures, GPA, gender and vocational track). The correlation between predicted and observed values are 0.70. Results are robust with and without this student.

Table 5
Treatment Effect on Effort in Session 3.

	Score on First 10 Questions		Score on First 20 Questions		Score on All 34 Questions	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.121 (0.126)	0.193* (0.089)	0.057 (0.126)	0.134 (0.085)	0.012 (0.126)	0.089 (0.086)
GPA		−0.036 (0.072)		0.004 (0.068)		−0.028 (0.069)
Math grade		0.542** (0.067)		0.582** (0.063)		0.551** (0.064)
Vocational track		−0.643** (0.110)		−0.542** (0.103)		−0.602** (0.106)
Female		−0.081 (0.092)		−0.134 (0.086)		−0.176* (0.088)
Older than 16		0.492** (0.184)		0.464** (0.172)		0.304* (0.176)
Baseline Growth Mindset		0.021 (0.048)		0.068 (0.045)		0.102* (0.046)
R-squared	0.000	0.506	0.003	0.567	0.004	0.544

Notes: * $p < 0.10$, * $p < 0.05$, ** $p < 0.01$. First row lists the dependent variable. Each column presents a separate regression and reports the estimated coefficient (robust standard error) for included covariates. All included covariates are reported, except from in columns 2, 4 and 6 where we additionally control for question assignment order (two indicators). Session 3 sample ($n = 254$).

growth mindset. Indeed, treatment increases the score by 56 percent of a standard deviation. In Column 2 we can see that this finding is robust to controlling for our pre-intervention variables, including baseline growth mindset.

In columns 3–6, we investigate how treatment affected challenge seeking when students had to create their own math worksheet in Session 2. As explained in Section 3.1, challenge seeking is measured as the number of “very hard” or “somewhat or very hard” questions chosen. The challenge seeking measures are standardized with mean zero and standard deviation one using the Session 2-sample. In Column 3, we see that treated students chose significantly more “very hard” questions compared to students in the control group. We can see that the estimate is robust to controlling for our pre-intervention variables in Column 4. It suggests that treatment increases challenge seeking by 29 percent of a standard deviation. In Columns 5 and 6, we use number of “somewhat hard” or “very hard” questions as the outcome measure, and we get a similar treatment effect on this measure.

The effect sizes in Table 4 are slightly larger than similar effect sizes obtained in evaluations of the same materials conducted in the United States. A recent evaluation with 76 high schools and over 16,000 students found an effect on self-reported mindset equal to 34 percent of a standard deviation and an effect on challenge-seeking of 23 percent of a standard deviation (Yeager et al., 2016). An evaluation in 11 high schools with 3276 students showed an effect on self-reported mindset of 30 percent of a standard deviation (Paunescu et al., 2015). The present effects seem to exceed the effect sizes in the United States, perhaps because students paid greater attention to the materials in the Norwegian context.

In Table 5, we investigate how treatment affected effort in the algebra questions in Session 3. Since some students did not have time to finish all the questions, or “gave up” – clicking fast through the questions,⁹ we look at how many correct answers students had on the first 10, 20 and all 34 questions. The measures are standardized with mean zero and standard deviation one using the Session 3 sample. In Column 1, we see no significant difference in effort on the first 10 questions. However, when controlling for baseline variables in Column 2, we can see that treated students have significantly more correct answers on the first 10 questions compared to students in the control group. Consistent with Hypothesis 1, the estimate suggests that treated students scored 19 percent of a standard deviation higher than control students. There were no significant differences between treated and control when investigating treatment effects on the first 20 or all 34 questions in Columns 3–6, suggesting no strong treatment effect on the overall sample.

In Table 6 we investigate treatment effects for different subsamples. First, we characterize the students to have either a fixed or a growth pre-intervention mindset by splitting the sample at the mean of our mindset measure. Consistent with Hypotheses 2, Panels A and B demonstrate that the treatment effect detected in Column 2 of Table 5 is entirely driven by students who initially had a fixed mindset. For these students, the treatment effect is large and significant for all three outcome measures. The estimates suggest that treated students scored 35, 34 and 29 percent of a standard deviation higher than control students on the first 10, 20 and all 34 questions, respectively. For students who initially had a growth mindset, there is no significant treatment effect; the estimated coefficient is even negative in all but one column.

In the remaining panels of Table 6 we investigate if readily observable variables from registry data can help us identify students particularly responsive to treatment. Recall that Table 3 demonstrated that, prior to treatment, a fixed mindset is

⁹ Eighteen students (7 percent) did not finish all questions. Among the 236 students who finished all questions, the average time per question declined. The first 13 questions took just under 50 s per question; questions 14–20 took on average about 40 s per question; questions 21–27 took about 30 s per question, and students spent just over 20 s per question on the remaining questions.

Table 6
Treatment Effect on Effort in Session 3. Subsample analyses.

	Score on First 10 Questions		Score on First 20 Questions		Score on All 34 Questions	
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Panel A: Pre-Treatment Fixed Mindset (n = 130)</i>						
Treatment	0.297 ⁺ (0.178)	0.348 [*] (0.135)	0.299 ⁺ (0.170)	0.335 ^{**} (0.117)	0.245 (0.170)	0.285 [*] (0.116)
Adj R-squared	0.014	0.434	0.016	0.538	0.008	0.540
<i>Panel B: Pre-Treatment Growth Mindset (n = 124)</i>						
Treatment	-0.094 (0.165)	0.022 (0.114)	-0.227 (0.172)	-0.059 (0.119)	-0.266 (0.169)	-0.129 (0.121)
Adj R-squared	0.005	0.553	0.006	0.563	0.012	0.530
<i>Panel C: Vocational Track (n = 133)</i>						
Treatment	0.234 ⁺ (0.133)	0.272 [*] (0.128)	0.217 ⁺ (0.117)	0.253 [*] (0.109)	0.222 ⁺ (0.119)	0.251 [*] (0.114)
Adj R-squared	0.016	0.131	0.018	0.189	0.018	0.143
<i>Panel D: Academic Track (n = 121)</i>						
Treatment	0.172 (0.162)	0.088 (0.122)	0.056 (0.178)	-0.029 (0.116)	-0.043 (0.173)	-0.110 (0.121)
Adj R-squared	0.001	0.449	0.008	0.584	0.008	0.524
<i>Panel E: Low GPA (n = 129)</i>						
Treatment	0.180 (0.135)	0.286 [*] (0.128)	0.156 (0.115)	.226 [*] (0.108)	0.121 (0.114)	0.191 ⁺ (0.106)
Adj R-squared	0.006	0.146	0.007	0.165	0.001	0.171
<i>Panel F: High GPA (n = 125)</i>						
Treatment	0.148 (0.165)	0.074 (0.125)	0.053 (0.169)	-0.030 (0.123)	-0.006 (0.174)	-0.078 (0.131)
Adj R-squared	0.002	0.458	0.007	0.496	0.008	0.459
Control variables included	No	Yes	No	Yes	No	Yes

Notes: ⁺ p < 0.10, ^{*} p < 0.05, ^{**} p < 0.01. First row lists the dependent variable. Each panel represents a different sample. For given sample, each row presents a separate regression and reports the estimated treatment coefficient (robust standard error) and adjusted R-square. Last rows indicate whether the regression includes the control variables. The control variables are GPA, math grade, vocational track (indicator), female (indicator), older than 16 (indicator), and question assignment order (two indicators).

particularly prevalent among students with low GPA and students in the vocational track. This is also clearly communicated in the tabulations in [Tables A1 and A2](#) in the [Appendix A](#). Thus, we investigate treatment effects splitting the sample based on track and GPA (at the median).¹⁰

In Panel C, we can see that among students in the vocational track there is a large and significant treatment effect. Looking at the first 10, 20 and all 34 questions, the treatment effect is 27, 25 and 25 percent of a standard deviation, respectively. Students in the academic track scored higher than other students, and as we show in Panel D, there is no significant treatment effect for them.

In Panel E we investigate treatment effects for students with a low pre-treatment GPA. We see that there is a significant treatment effect on all three outcome measures. Panel F demonstrates that there is no significant treatment effect on the students with a high pre-treatment GPA.

Since our most interesting results are in the vocational track and low GPA samples, [Appendix A Tables A3–A5](#) provide the balance tests, in addition to effect estimates on Session 2 outcomes, for these subsamples. From the balance tests in [Tables A3 and A4](#) we find that both subsamples are well balanced across treatment status on all characteristics, with the exception of significant differences in Females and Older than 16 in the vocational track sample, and in Female and Vocational track in the low GPA sample. Hence, all our reported estimates are controlled for all observables. [Table A5](#) demonstrates that also in these subsamples there are large and significant effects on the measures of growth mindset and challenge seeking in Session 3, and the magnitudes are similar to the magnitudes estimated for the full sample.

¹⁰ The correlation between having a high GPA and choosing the academic track in high school is 0.56. Even if this correlation is high, the overlap is by no means perfect, and consequently informative to split the sample both based on track and GPA.

6. Discussion and conclusion

Our results provide evidence that students' beliefs in their ability to learn are predictive of their subsequent perseverance. Moreover, we find evidence that these beliefs are malleable. As in prior studies, we only find effects on students who previously had a fixed mindset or had low achievement prior to the intervention. We find strong impacts of our treatment on these students' subsequent performance in a real effort task consisting of solving difficult algebra questions. To our knowledge, our paper is the first to draw a link between real-effort academic performance and experimentally manipulated academic mindset. Our paper joins a chorus of other interventions demonstrating that behavioral training can affect student outcomes (e.g. [Alan et al., 2016](#); [Duckworth and Seligman 2005](#); [Durlak et al., 2011](#)). While we can identify the impacts of mindset, we are unable to distinguish whether the formation of mindset came from education about the mind (Session 1) or social pressure and norms to improve mindset (Session 2).

There are several implications to our research. First and foremost, improving student performance through a low-cost informational treatment has policy implications for schools and teachers. If teachers and schools can improve students' growth mindsets, academic performance, especially among the poorest performing students, can be raised. In the context of Norway where students choose vocational or academic tracks, the finding suggests opportunities to improve students' mindsets earlier in their career, potentially influencing their choice of tracks. Second, implementation costs of the treatment are very low: Rather than improving students' opportunities to learn through costly structural changes, it leads them towards better utilization of the learning opportunities already within the educational system ([Yeager and Walton, 2011](#)).

We only track students over a five-week period, and it remains to be seen whether the impacts we observe represent a change in students' beliefs and behavior beyond the five weeks or whether the observed impacts will attenuate over time. We hope that our partnership with the school district might shed light on these more long-run impacts in future studies. We hope to look at different measures of academic achievement, academic choices, labor market participation and wellbeing.

While the impact of academic mindset is relatively new to economics, many of its core elements – the willingness to take risks for potentially beneficial reasons, the perceived cost/benefit of effort, and the willingness to sacrifice current leisure for future benefits – have a long history of being studied in economics. Our hope is that future research can provide a tighter link between these complimentary literatures.

Appendix A.

Table A1

Cross Tabulation of Pre-Intervention Mindset and Track in High School. Session 3 sample.

	Fixed mindset	Growth mindset	Total
Vocational track	74	59	133
Academic track	50	71	121
Total	124	130	254

Table A2

Cross Tabulation of Pre-Intervention Mindset and GPA. Session 3 sample.

	Fixed mindset	Growth mindset	Total
Low GPA	79	50	129
High GPA	45	80	125
Total	124	130	254

Table A3

Descriptive Statistics and Balance Test. Subsample Vocational Track.

	Session 1			Session 2			Session 3		
	Control	Treatment	Difference	Control	Treatment	Difference	Control	Treatment	Difference
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
GPA	-0.332 (0.869)	-0.469 (0.988)	-0.137 (0.125)	-0.232 (0.752)	-0.313 (0.814)	-0.081 (0.118)	-0.271 (0.899)	-0.372 (1.040)	-0.101 (0.168)
Math grade	-0.330 (0.831)	-0.446 (0.880)	-0.116 (0.115)	-0.275 (0.824)	-0.322 (0.849)	-0.047 (0.127)	-0.320 (0.782)	-0.324 (0.900)	-0.004 (0.146)
Female	0.382 (0.488)	0.546 (0.499)	0.164* (0.067)	0.378 (0.488)	0.559 (0.499)	0.181* (0.075)	0.508 (0.504)	0.661 (0.476)	0.154+ (0.085)

Table A3 (Continued)

	Session 1			Session 2			Session 3		
	Control	Treatment	Difference	Control	Treatment	Difference	Control	Treatment	Difference
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Older than 16	0.118 (0.324)	0.092 (0.290)	-0.025 (0.042)	0.085 (0.281)	0.021 (0.145)	-0.064+ (0.035)	0.108 (0.312)	0.073 (0.262)	-0.034 (0.050)
Fixed Mindset 1	0.166 (1.045)	0.017 (1.017)	-0.148 (0.139)	0.086 (1.043)	-0.008 (1.012)	-0.095 (.156)	0.189 (1.048)	-0.066 (1.009)	-0.256 (0.178)
Fixed Mindset 2	0.098 (1.036)	0.028 (1.062)	-0.069 (0.141)	0.058 (1.040)	0.017 (1.048)	-0.040 (0.158)	0.091 (0.984)	0.044 (1.058)	-0.046 (0.177)
Fixed Mindset Math	0.177 (1.114)	-0.020 (1.030)	-0.197 (0.145)	0.101 (1.074)	-0.097 (1.006)	-0.198 (0.158)	0.212 (1.053)	-0.002 (1.014)	-0.214 (0.179)
Fixed Mindset Effort	0.047 (1.057)	0.133 (1.144)	0.087 (0.148)	-0.073 (0.981)	0.073 (1.098)	0.147 (0.157)	-0.008 (1.062)	0.166 (1.166)	0.174 (0.193)
Baseline Growth Mindset	-0.171 (1.076)	-0.049 (1.019)	0.121 (0.142)	-0.065 (1.028)	0.009 (0.969)	0.074 (0.151)	-0.173 (1.046)	-0.041 (1.019)	0.131 (0.179)
N	102	119	221	82	93	175	65	68	133

Notes: For each session sample, columns provide the mean (and standard deviation) for the control group, and the treated group, and the estimated coefficient (robust standard error) from regressing each covariate against treatment status. + p < 0.10, * p < 0.05, ** p < 0.01

Table A4
Descriptive Statistics and Balance Test. Subsample Low GPA.

	Session 1			Session 2			Session 3		
	Control	Treatment	Difference	Control	Treatment	Difference	Control	Treatment	Difference
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
GPA	-0.507 (0.757)	-0.661 (0.941)	-0.154 (0.117)	-0.437 (0.615)	-0.494 (0.718)	-0.057 (0.106)	-0.450 (0.774)	-0.552 (0.928)	-0.102 (0.150)
Math grade	-0.493 (0.727)	-0.628 (0.731)	-0.135 (0.101)	-0.450 (0.701)	-0.536 (0.713)	-0.086 (0.112)	-0.469 (0.687)	-0.550 (0.727)	-0.081 (0.124)
Vocational track	0.808 (0.393)	0.891 (0.311)	0.083+ (0.049)	0.802 (0.400)	0.914 (0.281)	0.112* (0.055)	0.738 (0.442)	0.843 (0.365)	0.105 (0.071)
Female	0.343 (0.477)	0.468 (0.501)	0.125+ (0.067)	0.315 (0.467)	0.475 (0.502)	0.159* (0.077)	0.446 (0.500)	0.531 (0.502)	0.085 (0.088)
Older than 16	0.121 (0.328)	0.108 (0.311)	-0.013 (0.044)	0.078 (0.271)	0.024 (0.155)	-0.054 (0.035)	0.123 (0.331)	0.078 (0.270)	-0.044 (0.053)
Fixed Mindset 1	0.250 (1.009)	0.057 (1.027)	-0.193 (0.140)	0.233 (0.977)	0.022 (1.021)	-0.210 (0.159)	0.291 (0.966)	0.044 (1.018)	-0.247 (0.174)
Fixed Mindset 2	0.231 (1.024)	0.123 (1.039)	-0.108 (0.142)	0.260 (1.009)	0.114 (1.024)	-0.145 (0.161)	0.317 (0.956)	0.236 (1.042)	-0.080 (0.176)
Fixed Mindset Math	0.194 (1.125)	0.0159 (1.038)	-0.178 (0.149)	0.149 (1.095)	-0.063 (1.006)	-0.213 (0.167)	0.188 (1.085)	0.053 (0.993)	-0.135 (0.183)
Fixed Mindset Effort	0.167 (1.052)	0.245 (1.138)	0.077 (0.151)	0.046 (0.942)	0.215 (1.101)	0.168 (0.162)	0.072 (1.014)	0.340 (1.141)	0.267 (0.190)
Baseline Growth Mindset	-0.291 (1.067)	-0.144 (1.000)	0.147 (0.143)	-0.242 (0.991)	-0.090 (0.946)	0.151 (0.154)	-0.304 (0.999)	-0.220 (0.965)	0.084 (0.173)
N	99	111	210	76	82	158	65	64	129

Notes: For each session sample, columns provide the mean (and standard deviation) for the control group, and the treated group, and the estimated coefficient (robust standard error) from regressing each covariate against treatment status. + p < 0.10, * p < 0.05, ** p < 0.01

Table A5
Treatment Effect on Post-Treatment Mindset and Challenge Seeking in Session 2, by subsamples.

Subsample	Post-Treatment Growth Mindset		Choosing "Very Hard" Challenge Questions		Choosing "Hard" or "Very Hard" Challenge Questions	
	(1)	(2)	(3)	(4)	(5)	(6)
	Vocational track	Academic track	Vocational track	Academic track	Vocational track	Academic track
Treatment	0.455** (0.127)	0.656** (0.129)	0.259+ (0.145)	0.256 (0.159)	0.295+ (0.153)	0.257+ (0.150)
GPA	0.001 (0.099)	0.301 (0.207)	-0.008 (0.113)	-0.111 (0.256)	-0.122 (0.120)	0.013 (0.240)
Math grade	0.261** (0.091)	0.105 (0.119)	0.148 (0.105)	0.748** (0.147)	0.223* (0.111)	0.645** (0.138)
Female	-0.010 (0.129)	-0.003 (0.139)	-0.496** (0.148)	-0.327+ (0.172)	-0.543** (0.156)	-0.214 (0.162)

Table A5 (Continued)

Subsample	Post-Treatment Growth Mindset		Choosing “Very Hard” Challenge Questions		Choosing “Hard” or “Very Hard” Challenge Questions	
	(1) Vocational track	(2) Academic track	(3) Vocational track	(4) Academic track	(5) Vocational track	(6) Academic track
Older than 16	0.291 (0.282)	0.287 (0.405)	−0.269 (0.324)	0.322 (0.500)	−0.161 (0.343)	0.427 (0.469)
Baseline Growth Mindset	0.516** (0.064)	0.522** (0.075)	−0.043 (0.073)	0.255** (0.093)	0.008 (0.077)	0.078 (0.087)
R-squared	0.3791	0.4879	0.0627	0.3879	0.0732	0.3369
N	174	114	175	114	175	114

Notes: † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$. First row lists the dependent variable. Each column presents a separate regression and reports the estimated coefficient (robust standard error) for all included covariates.

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