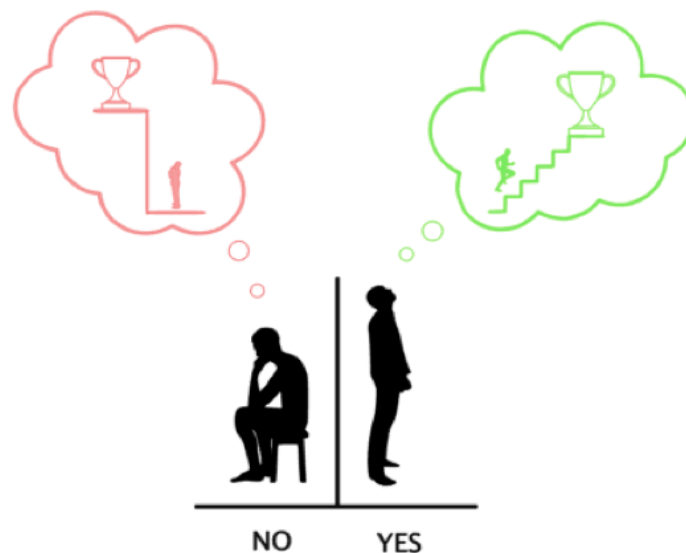




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Is your mind set for programming?

An experimental one-session study examining if treatment effects from growth mindset stimulation increase growth mindset and performance on a programming task



Source: (Nybø & Kahrs, 2019)

Master of Science in Business Administration
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Is your mind set for programming?
An experimental one-session study examining if treatment effects from growth mindset
stimulation increase growth mindset and performance on a programming task

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Abstract

The rapid pace of technological innovation has created a demand for higher technological knowledge. However, it seems like a lot of people are hesitant to acquire these highly needed skills. Research has shown that people's beliefs in intelligence and abilities affect performance, and having a growth mindset, compared to a fixed mindset, increases willingness to learn and embrace challenges (Dweck, 2012).

In a one-session experiment we investigate if using protocols from psychology changes the treated student's beliefs in their ability to learn how to program a simple calculator, and if the growth mindset intervention positively affect performance, compared to the control group.

We find treatment effects on both growth mindset of intelligence and mindset of effort beliefs, with the highest increase in mindset of effort beliefs post intervention. This increase in effort beliefs is also largest for the treated students who already had a growth mindset pre-treatment. We found no link between the growth mindset intervention and the programming task, as the treated participants scored 0,756 points lower than the control group. This can be explained by growth mindset not having an effect on programming performance or due to weak validation of the programming task, such as weak test of performance.

These findings suggest that a one-session growth mindset intervention increases growth mindset for the treated participants, which can increase the willingness to embrace challenges, thus reduce hesitation to learn new skills, and increase willingness to put effort into learning.

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1. Introduction

Due to the rapid pace of technological innovations, a demand for higher skills and knowledge in computer science has emerged. Simple jobs, with narrow job designs, are replaced with automation, creating a greater need for complex jobs with enriched design. For example, in the US, the demand for software developers is predicted through 2022 to grow at twice the rate of the average occupation, indicating a significant rise in demand for programming skills (Loksa et al, 2016). To keep up with this shift in the labor market, it is crucial for both organizations and individuals to acquire a mindset that fosters continuous learning and development.

The mindset of individuals, how they perceive their abilities, greatly influences learning and how tasks and challenges are approached and performed. Because people have different mindsets, they will react differently to the same situations. For example, when presented with a new learning situation, some people will thrive, while others will dread the situation. Dweck (2012) describes that these two reactions can be explained by having a growth or a fixed mindset. People with a growth mindset view their intelligence and abilities as malleable, that they can be developed and improved over time, with effort. People with a growth mindset welcome a challenge, and views it as a learning opportunity. People with a fixed mindset believe that their intelligence and abilities are fixed and are something about you that you are not able to change. They view failure as a limitation of their ability, and would rather not put any effort into anything they might fail. Research shows, that depending on their mindset, there is a significant variation in both how people approach tasks, and the following performance (Rege et al, 2018).

One prominent obstacle restricting people with a fixed mindset to develop is their fear of making mistakes and not managing the task. A growth mindset intervention uses protocols from psychology to stimulate people's mindset to understand that the brain is malleable, and that they can develop by learning new skills and by taking more risks. The purpose is to help people become more willing to learn, and reduce the fear and hesitation of trying new things. We know from previous studies that growth mindset interventions increase the treated participants growth mindset and performance. The treatment effect on performance has shown to be especially prominent for low performing students (Blackwell et al.,2007, Bettinger, Ludvigsen, Rege, Solli & Yeager, 2018). Most growth mindset interventions are performed

on tasks the students already have some training and knowledge of, so, the value we add to this research is investigating how the mindset intervention affect participants performance when they are asked to learn and perform a complex task they had no previous knowledge of, in this case; how to program a simple calculator.

We chose to create a programming task because programming is something people in general find difficult and overwhelming to comprehend. It is similar to mathematics, a subject that builds on previously learned material. If you lack knowledge in some parts of the subject, it will most often lead to lower achievement over time (Blackwell et al, 2007, Bettinger et al. 2018). As explained by Blackwell et al. (2007), a task needs to be sufficiently challenging to trigger patterns related to the theory of intelligence and effort beliefs, and programming fulfills these criteria's. Also, as the technology and labor market develops, it is highly relevant in today's society.

We also chose a one-session intervention, as DeBacker et al (2018) found evidence that this can be just as effective as interventions with several sessions, and produce similar results in increased growth mindset as Blackwell et al. (2007) and Bettinger et al., (2018) did. However, we are curious to examine the effects of a one-session growth mindset intervention on the students' pre-treatment mindset, and if giving the students more of a growth mindset will increase their performance on the effort task of programming. Our experiment is a modified version of the baseline measures and intervention used in Bettinger et al. (2018), which is originally developed by Yeager et al. (2016). The Bettinger et al. (2018) intervention is adapted to Norwegian language and context, in which we have further modified into a one-session intervention targeted towards our participants.

The experiment consists of four parts; pre-intervention mindset measure, the intervention, a real effort task, and post-intervention mindset measure with some demographic questions.

First, the student's mindset will be measured at baseline, by having the students' rate four statements on a four-point Likert scale to determine if they have more of a fixed or growth mindset.

Second, in the growth mindset intervention the participants are randomized into two groups, one treated with a growth mindset intervention, and one control group presented with basic information about the brain. The treated group will be taught that the brain is malleable and

that abilities and performance are developable, when putting effort into learning and practicing over time. (Dweck and Yeager, 2019).

Third, after the intervention, the real-effort task of programming is undertaken. Our experiment is designed to test the effect of a growth mindset intervention on a task the participants have no prior knowledge of. The participants are asked to learn how to program a simple calculator with a two-page written instruction, followed by ten multiple choice questions regarding what they just learned.

Lastly, after the intervention and the programming task, we measure mindset once more to see if the treated participants have changed their mindset after the intervention. In addition, we collect some demographic information for our analysis like gender, age, study direction, and both their own and parent's education levels.

For our analysis, we create baseline measures for pre- and post-treatment growth mindset of intelligence and effort beliefs to examine the effects of the growth mindset intervention on the treated participant's mindset. The participant's performance is measured by the real-effort programming task; by the score on the ten multiple-choice questions, the time spent on reading the instruction and the time answering each question. We compare the treatment and control group to see if the growth mindset intervention increases performance on the task, and if there is a link between their mindset and performance.

In addition, in our subsample analysis, we split the participants into two groups based on study directions, one named science, technology, engineering, mathematics (STEM) and Business studies, with more technical and analytical subjects, and one called Social studies, with less of these subjects. We have also looked at the difference in participants with mothers having lower and higher education levels. We choose to look at these subsamples as Bettinger et al, (2018) found evidence that students choosing academic tracks display more of a growth mindset and generally performed better, than students choosing vocational tracks. We therefore wanted to examine if there were any differences within different academic study directions, both in mindset and if there is a difference in performance on the programming task for the treated participants. Parents' education level has also shown to be a good predictor of children's performance. Especially for girls the mothers' education level is a predictor of performance (Glick & Sahn, 2000). Since we found the parent's education level to have a positive correlation, we choose to look closer at only mothers' education level and the treated participant's mindset and performance.

Our results show significant treatment effects on both the growth mindset of intelligence and growth mindset of effort beliefs. The presence of a growth mindset pre-treatment was higher for growth mindset of intelligence, than growth mindset of effort beliefs, especially for Social studies students. The largest increase in growth mindset post-treatment, is found in effort beliefs, for students with pre-treatment growth mindset of intelligence and effort beliefs. It is interesting that the increase in a growth mindset of effort beliefs is larger for the treated students who already possess a growth mindset pre-treatment, but at the same time it makes sense, as these are the students already paying the most attention to what they are presented in the intervention.

The results from the effort task are not what we expected, and do not support other research on growth mindset intervention and effort tasks. Previous research has found a strong link between having a growth mindset and performance (Blackwell et al., 2007; Bettinger et al., 2018; Dweck & Yeager, 2019) We expected the intervention to increase performance on the programming task, however, the treated participants did worse than the control group. Hence, it appears to be a negative correlation between a growth mindset intervention and performance on the programming task. We found growth mindset to increase post-intervention for treated students, but performance on the programming task is weaker for treated students. This suggests that the intervention has no, or even a negative, impact on performance in the programming task.

There are two possible explanations for the result on the programming task; the first is that having a growth mindset does not play a role in performance in programming. The second explanation is a poor test of performance in programming or a weak validation of the programming task. As most participants scored well on the test, with a mean score of 7,94, it seems as most people could have managed our task well, regardless of mindset. The distribution of score should preferably have been a normal distribution, but was skewed to the right. We should have had more time to validate the effort task and had an additional pilot tests with more participants. We also offered a monetary reward for each correctly answered question for all participants, which may have contaminated the treatment effect. Because we found treatment effects on mindset, but a negative treatment effect on the programming task there is a need for further research to investigate if the treatment effect on performance is

because of the weaknesses in the validation of the task, and if improving this, can create a positive correlation on mindset and performance in programming.

The results are interesting as it validates that a one-session growth mindset intervention increases a growth mindset for treated participants. As previous research has shown, this should increase the treated participants willingness to take risks, and reduce hesitation try new things and promote learning, thus increase development and improvement on different tasks they put effort into. Programming is highly relevant in today's society, and further research could add important value and knowledge for recruitment to this area, as of the increasing need for people with these skills in the labor market.

2. Theoretical Framework

2.1 Growth Mindset

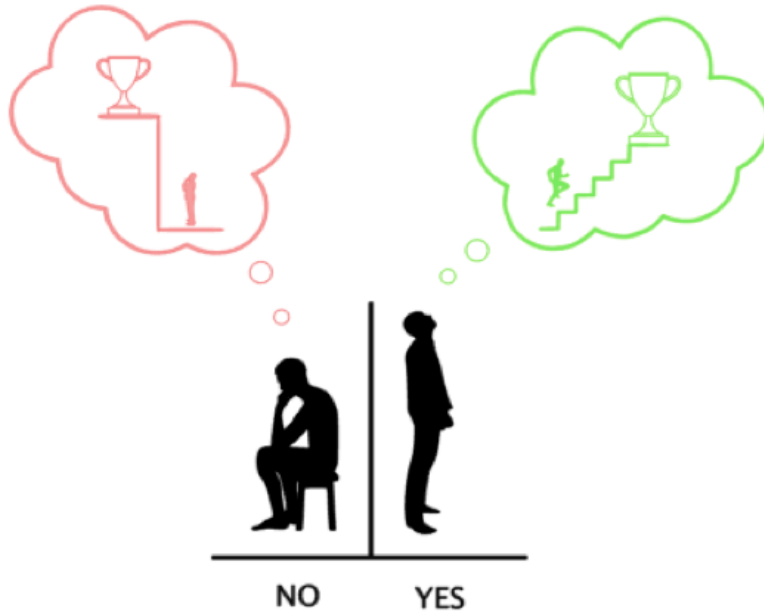
Research about mindset began in the early 1980s when C. Dweck and M. Bandura wanted to answer the question of why students with equal abilities and talents had different thoughts about their abilities (Dweck and Yeager, 2019). During this research, Dweck developed theories about two different views of abilities that she called implicit theories of intelligence. She used implicit because she believed that people were not aware of them. These two intelligence mindsets are defined by people's belief in their abilities and talents and are essential for how people face challenges, further develop skills, and the success of the task at hand. It is important to be aware that a person not necessarily always has either a growth or a fixed mindset; it may alter based on the setting or situation (Dweck, 2009).

Those who believe that their abilities, intelligence and talents are given, have what Dweck calls a fixed mindset. A person with a fixed mindset will see failure as a limit of their abilities, and will instead stick to what they know, thus put minimum effort into learning something new (Dweck, 2009). Generally, those with a fixed mindset are less open to changes, avoid new tasks and learning opportunities because they are afraid they might fail. They also often tend to try to hide what they find difficult or not excel in, and persistence often diminishes. When they resist asking for help, because this might disclose their lack of ability or talent, they will most likely never reach their full potential.

On the other hand, are those who believe that abilities, intelligence, and talents can develop and improve over time through practice and hard work (Dweck and Yeager, 2019). They have what Dweck calls a growth mindset. Those with a growth mindset are more likely to take on challenges and learning possibilities. They show persistence and a willingness to improve their skills and see failure as an opportunity to grow. They like to try new things, and thus do not mind putting in some extra effort to reach their goals. People with a growth mindset are also more willing to unveil the things they find difficult, to get help and advice to further develop and improve. Research has shown that they have a healthier attitude towards learning and practice, hunger for feedback, manage their time better, deal better with setbacks, and their performance is significantly better. People with a growth mindset believe that feedback is an indispensable roadmap that shows their deficiencies and is a chance for improvement; thus the performance is being enhanced significantly over time (Dweck, 2009).

To illustrate the differences in how the two mindsets influences how a person perceives a problem and the road to reach their goal we made the illustration in figure 1. This figure shows that if you have a growth mindset you are eager to work and find solutions toward reaching your goal, whereas for a person with a fixed mindset the limitations are in focus, making it harder to see that the goal is achievable and thus might not put in the effort needed to reach the goal.

Figure 1: Difference in a Fixed and a Growth Mindset



Notes: We made this figure to illustrate how the two mindsets affect perception and goal achievement. With a fixed mindset, illustrated to the left, the process from start to finish seems long and unattainable, and the desire to put in any effort is small, whereas a growth mindset, illustrated to the right, sees strategies and ways to put in the effort to reach the goal.

Further research in mindsets have also revealed that fixed and growth mindsets also apply to beliefs about people's personalities, stereotyping, people's judgment towards others and their behavior against them (Dweck & Yeager, 2019). Dweck and colleagues found that people with a fixed mindset, more often than those with a growth mindset, tend to take traits about another person and make strong forecasts about what that person would do in the future. Five studies by Levy, Stroessner, and Dweck (1998) found that people with a fixed mindset made stronger stereotypical judgments on different groups, and hold on to group labels more firmly than those with a growth mindset. For example, a study done by Heslin, Latham & VandeWalle (2005) investigated whether a manager's mindset affected his or her appraisal of both a positive and adverse change in employee performance. They examined if the managers revised their initial judgment about the employee by first viewing three poor performances by an employee, and then three good performances. They also conducted a second experiment while changing the order and showing the employees good performance first. They found that people with a fixed mindset were reluctant to change their first opinion about the employee,

even when they watched the good performance first. This shows that growth mindset appears to explain why some managers notice and acknowledge employee improvements, while managers with a fixed mindset hold on to their initial opinion.

2.2 Developing Learners

When people are taught the belief that personal characteristics are developable, their growth mindset and willingness to learn increases. To excel, people need to be presented with a mindset that represents challenges as something they can work on and overcome over time, with patience, new strategies, effort, learning, and help from others (Dweck & Yeager, 2012). When people's potential to change is emphasized, effort and perseverance increases (Bettinger et al., 2018).

Even though there is a vast majority of easily accessible learning opportunities some people seem reluctant to take advantage of these. For example, the National Research Council (2010) have established that math literacy, which can be applied broadly, is proven to increase logical reasoning. However, in a survey by the Raytheon Company (2012) nearly two-thirds of US 9th graders chose to avoid a challenging math assignment when possible. As the purpose of education is to expand knowledge it is worrisome that students chooses to not fully take advantage of their learning possibilities.

For example, a study by Rege et al., (2018) testing a growth mindset intervention on challenge seeking presents evidence that students given the growth mindset intervention manifests higher challenge seeking behavior relative to the control group ($d_s = .20$ to $.24$). Treatment effects were also present when students were presented with enrollment in advanced math classes, a real-life challenge-seeking behavior. The effects were even higher when entry into advanced math classes was made more accessible after receiving the intervention. These results show that a growth mindset intervention increases the willingness to be a "learner," the willingness to exert more effort and find solutions when the task at hand becomes difficult.

2.3 The brain's malleability

An important implication from the mindset research is that a growth mindset and its benefits can be encouraged by teaching that learning is a process, and in the processes towards

learning one can “grow the brain” and increase intellectual abilities (Dweck, 2015). A lot of work done in psychology and neuroscience shows the brains tremendous plasticity – its ability to change, adapt and grow when people work hard to develop a set of skills. The brain can change how it is “wired” and the way it functions (Moller, 2009). When learning new tasks, the senses involved in the learning process form new synapses that leaves permanent traces in the brain, which may be active and present for a lifetime. In growth mindset interventions, the metaphor that the brain is like a muscle is often used to illustrate that it grows and develops when used. This metaphor makes it easier for people to understand the brain's ability to change and grow, as most people know that exercising causes larger muscles and improve manual skills (Bettinger et al., 2018).

2.4 Growth Mindset Interventions

Following the extensive theoretical research on intelligence mindset, interventions have been developed to measure if mindsets can be changed, and if motivation and behavior can be altered under certain conditions (Dweck and Yeager, 2019). A growth mindset intervention is made to alter people’s mindset, so they are able to reach their full potential. It is supposed to change your mindset to be less hesitant of learning new things, more open to changes, seek challenges, endorse learning opportunities and put in the effort needed to improve your skills.

Several studies have shown that implicit beliefs about intelligence can be altered under certain conditions (Dweck and Yeager, 2019, Bettinger et al., 2018). Yeager and Walton (2011) explain that successful interventions are carefully constructed by theoretically based experiences and research in psychology, meant to influence the target in an experimentally proven technique. They also emphasize that the interventions might be hard to replicate, as small changes in the environment or target population can alter the meaning and hence impede replication.

Most interventions that have been tried in education, as new curriculums, teacher-training models and school redesign, have found small to no effect on the students learning outcomes and performance (Dweck and Yeager, 2019). The largest effect found for these interventions is roughly 0,20 standard deviations, which is only equal to a small effect by Cohen (Cohen, 1998). These interventions are also costly for schools and take a lot of time to execute.

Some of the first growth mindset interventions were based on the brain's malleability using the memorable metaphor that the brain is like a muscle, which gets stronger with exercise (Bettinger et al. 2018). It also emphasized that it becomes even stronger when people learn new, challenging tasks. They have also found ways for students to internalize this growth mindset “message” by asking them to apply the material to their own lives. At first, the growth mindset interventions were given face-to-face, and it showed promising results in academic performance (Dweck and Yeager, 2019). However, face-to-face intervention is both time-consuming and expensive. Therefore, Dweck and colleagues wanted to see if a short online growth mindset intervention could shift students’ mindsets, and found an increase of around 0,10 grade points on lower-achieving students GPA.

When implementing new interventions to increase performance a concern is always how time-consuming it will be, and if the results will be good enough to defend both time use and cost. Newer research demonstrates that a single-session intervention can be equally effective as interventions with several sessions and longer timelines (DeBacker et al., 2018). Most of these one-session interventions use material from previously successfully implemented multiple sessions interventions. One-session interventions are also called one-shot interventions, and have been tried with several approaches, as face-to-face, paper-based and online interventions. They have also lasted from 10 minutes to one hour, which makes them attractive to use. These one-shot interventions have shown promising results, all from two days to three years after the intervention.

Several studies have shown that a growth mindset intervention alters the treated participant’s mindset to be less afraid of learning and trying new things, and more willing to seek challenges, put in the effort to reach their goals and evolve their skill sets (Dweck & Yeager, 2019; Bettinger et.al 2018; Blackwell et al. 2007). When people endorse more of a growth mindset, research shows that they perform better on different tasks and gain a higher GPA post-intervention. Especially lower-achieving students seem to benefit from the interventions in terms of higher grades, while already high-achieving students seem to benefit more in terms of for example choosing more difficult math classes (Dweck & Yeager, 2019). This research shows that there is a strong link between the growth mindset interventions and higher performances on tasks post-intervention.

2.5 Changes in the Labor Market

Between 2015 and today, we have created more data than in all previous years, and it is developing at an incredible speed. The rapid pace of technological innovations has created significant changes in the labor market. As new technology advances, the need for different and unique competencies arises. As a result, “old” jobs become obsolete and “new” job descriptions are created. For example, when a warehouse becomes automated, machines replace the people doing well-defined routine tasks, and new jobs are created to operate these machines (Kaasa 2016).

Job descriptions with more defined problems and simple routine tasks are now, to a more considerable extent, replaced with jobs requiring more problem-solving and complex skills. Simple routine tasks are replaced by machinery, as they do the job both cheaper and faster. The classical approach within job design, which emphasizes proficiency, optimization of specific tasks and low skills, is becoming more and more obsolete. Companies are moving more towards a modern approach, emphasizing employee learning, problem-solving and high-level decision-making (Laezar & Gibbs, 2014). Therefore, there is an increased need for people with different skill sets than before, and employees need training and education to keep up with the changes in the labor market.

The labor market shift in demand, from narrow to enriched job design, significantly increases the threshold of skills and knowledge people need to acquire. Thus, it is important for people to learn how to thrive in learning situations and pursue learning experiences that are effortful and challenging. Having the ability to cope with difficulty and a desire for challenges will enable people to gain and expand their abilities to work on complex work tasks (Rege et al., 2018). To address this shift in demand, learning is important, both individually and organizationally. Organizations need to stay competitive, and therefore need to train and retain employees with the right competencies to ensure that their workforce has the qualifications they need now and in the future.

2.6 Growth Mindset and Programming

Today, programming knowledge is in general seen as a necessary part of modern literacy. Computer programming is lines of code designed to send messages to a machine. The codes, which seems complicated and incomprehensible for most people, is designed to be efficient, translatable commands (Chavez, 2010). Mastering programming language is a difficult task,

as it requires you to be able to read, trace, explain and systematically write code (Schoeman, Gelderblom & Muller, 2013). However, programming is proven to foster and develop specific cognitive skills that positively affect problem-solving skills (Van Merriënboer & Krammer, 1987).

One strategy to comprehend this demanding way of thinking and solving problems is called computational thinking, which is “*aspects of designing systems, solving problems, and understanding human behaviors*” (Kafai & Burke, 2014, p.6). Thinking computationally can help people articulate and comprehend a large number of disciplines, not only math or science. It helps people think logically, by breaking down the different elements of any problem, to come up with a solution. For example, to teach children to think more rigorously and critically is not a new idea, and despite schools having had computers for many years, little progress has been made in programming education. Learning programming and how to write code increases an individual's capacity to participate in today's digital public, in social networks and communities, and is a form of expressing oneself.

However, though coding skills are recognized as necessary for current and future job demand and implemented as a part of the curriculum in high schools, students find the material too difficult, with a drop out rate of 30-50% (Loksa et al., 2016). Studies have even shown that introductory programming courses can put the students into a fixed mindset, convincing them that they do not have the abilities necessary to learn how to code. Even more concerning, the ripple effect of a student put into a fixed mindset because they fail coding classes, will not only defer them from learning how to code, but they will also most likely keep a fixed mindset in the future toward learning certain new skills (Loksa et al., 2016).

Q.Cutts, E.Cutts, Draper, O'Donnell & Saffrey (2010) study on mindset and programming propose that many students drop out of high school introductory programming classes because the students have fixed mindsets towards programming. The study carried out a six-week growth mindset intervention in a high school programming introductory class, in addition to writing growth mindset comments on returned paperwork. The results showed a significant change in mindset and test scores, both after the six-week intervention and at the exam at the end of the year.

Loksa et al., (2016) presents a study with a growth mindset intervention that focuses on explicit problem solving and learning strategies. The intervention shows an increase in growth mindset in addition to improved programming skills, self-efficacy, independence, and metacognitive awareness. The authors propose that how coding is taught is important for the students learning and mastery, and in addition to solely focusing on teaching programming languages and tools, the cognitive aspects of programming, such as growth mindset and learning strategies, should be taught.

The result from these studies within programming underlines the importance of further research on how to implement successful growth mindset beliefs in programming. When people possess a fixed mindset towards programming, the fear of failing and not managing the task becomes so strong, that people chose not to try if given the option. With a high drop-out rate and people hesitating to learn programming, there will not be enough people with a skill set within this field. There is therefore a need for further research to find a sufficient way of changing people's mindsets, to be more willing to seek challenges and try to learn new tasks. A growth mindset intervention has proven to create successful results in recruitment to more difficult math classes, and it is interesting to investigate whether it also could show promising results within programming.

3. Research Question

We are interested to test if a one-session growth mindset intervention alters the treated participants mindset towards more of a growth mindset, and if treatment effects will increase performance when the effort task is material that is new and challenging to the participant, in this case; learning how to program a simple calculator.

We present the following research question:

Will a one-session growth mindset intervention alter the treated participant's mindset towards more of a growth mindset, and will treatment effects increase performance on a programming task in which the material is challenging and new?

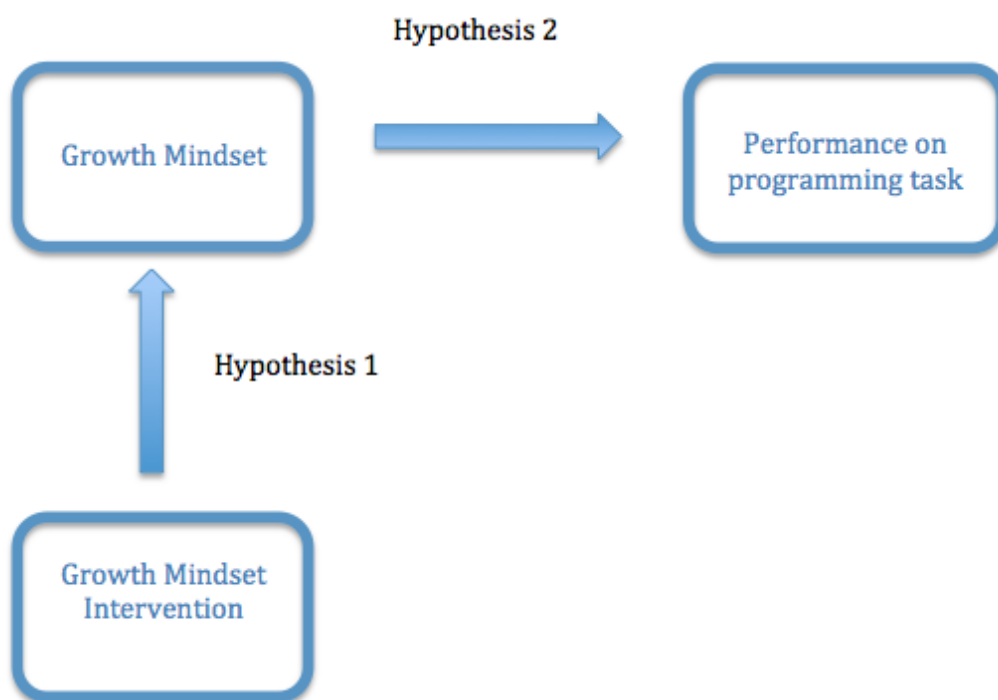
3.1 Hypotheses

We believe that if the growth mindset intervention increases a participant's beliefs in his abilities to learn, it will increase the marginal benefit of effort, and enhance performance on the real-effort task.

Hypothesis 1: The treatment effects on mindset will increase the treated participant's growth mindset compared to their mindset prior to the intervention.

Hypothesis 2: The treated participant's will perform better on the real-effort task, compared to the control group.

Figure 2: Illustrates our two hypotheses



In addition to our two hypotheses, we want to investigate if different subsamples are more responsive to the growth mindset intervention than others. Previous studies have found that students choosing academic tracks are more likely to endorse a growth mindset than students choosing vocational tracks (Bettinger et al., 2018). They have also found a strong link between a growth mindset and higher performance. We therefore wish to examine if there is any difference for students in Social studies and

STEM and Business studies as they are both in academic tracks. We would expect that students in STEM and Business studies to endorse more of a growth mindset than Social studies students, and that they perform better on the real-effort task of programming, as they have chosen subjects with more technical and analytical subjects.

Mothers' education level has previous shown to be a strong predictor for how well students do in school (Glick & Sahn, 2000). We therefore assume that students with higher educated mothers perform better on the real-effort task of programming, and wish to examine this further in a subsample analysis.

4. Experimental Design

4.1 Intervention and Measures

We developed a computer program with one four-part session with a duration of about 30 min. Part one measures the participant's mindset at baseline, and the second part introduces the intervention for the treatment group and control content for the control group. The third part consists of a real effort programming task in which the subjects read a step-by-step instruction on how to program a simple calculator using Java programming language, followed by ten multiple-choice questions regarding what they just learned. The last part measures mindset post-intervention and asks some demographic questions like age, study direction, and so forth.

Figure 3: Content of Computer Program

Pre-Intervention Measures	Intervention	Real-Effort task	Post-intervention measures
Baseline mindset measures	Treated: Mindset Control: Placebo	Instructions and Multiple-Choice Questions	Mindset Measures Demographic Questions

Our experiment is funded by the Business School at the University of Stavanger and the U-Say project, managed by professor in economics Mari Rege. This funding allowed us to pay the participants 100 NOK as a “show up fee” for completing the experiment and an additional 10 NOK for each correct answer on the ten multiple-choice questions. We chose to pay 100 NOK for the students to participate as an incentive to show up and do the experiment. The

additional 10 NOK for each correct answer was chosen as a monetary incentive to ensure that the participant's put real effort into participation and tried to do their best at the effort task. We chose this amount because if they answered correctly on 50% of the question, they would earn the equivalent to an hourly student wage in Norway for half an hour work. We debated this amount to be higher, but because we wanted 80-100 participants our budget wouldn't allow for more. We also debated lowering the participation amount to increase the amount for each correct answer on the multiple-choice questions, but were afraid people would choose not to participate if they thought the payout was not worth their time and effort. We also feared that a challenging task as programming would scare the students from participating, and that they would fear not to earn "enough" money to make it worth their time.

4.1.1 Mindset Measures

Part one of the experiment consists of creating a baseline mindset by measuring the students' mindsets pre-intervention. A low score indicates a fixed mindset, and a high score indicates a growth mindset. Using a 4-point Likert scale the students are asked to rate how strongly they agree (1) or disagree (4) with the four following mindset statements;

1. "You have a certain amount of intelligence, and you can't do much to change it"
(Fixed Mindset 1)
2. "Your intelligence is something about you that you really can't change very much"
(Fixed Mindset 2)
3. "Being a "computer or IT person" or not is something that you really can't change. Some people are good at computers and IT and other people aren't"
(Fixed Mindset IT)
4. "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 statements, measuring mindset, originally stem from Carol Dweck's research about different views of ability, called implicit theories of intelligence (Dweck and Yeager, 2019). This theory is divided into a theory of intelligence, effort beliefs and helpless responses to failure (Blackwell et al, 2007). In our experiment, our focus is on the theory of intelligence and effort beliefs. Dweck believes that thoughts based on experiences are not isolated ideas or

thoughts, but are a part of a meaning system that brings ideas, goals, beliefs and behavior together. The theory about effort beliefs is based on a belief that effort is a positive thing that develops your abilities. Also, when believing that intelligence is something you can improve and develop through hard work leads people to put in the extra effort to succeed and improve in the desired area/task.

The statements we use to measure the participant's mindset on intelligence and effort have been used and validated through extensive research, and shown to be good predictors for grades and performance (Yeager et al., 2016; Burnette et al., 2013; Blackwell et al (2007); Bettinger et.al 2018). The statements have been translated into Norwegian by Bettinger et al. (2018), which made it easy for us to use in our experiment, as it was held in Norwegian. However, we slightly altered statement three and four to measure the participants mindset towards computer science and IT. The original statement was previous used to measure participants' mindset on effort beliefs towards mathematics, but we changed it to better fit our real-effort task of programming. The wording is still the same; the only change is the type of skill/task we ask them about.

4.1.2 Intervention

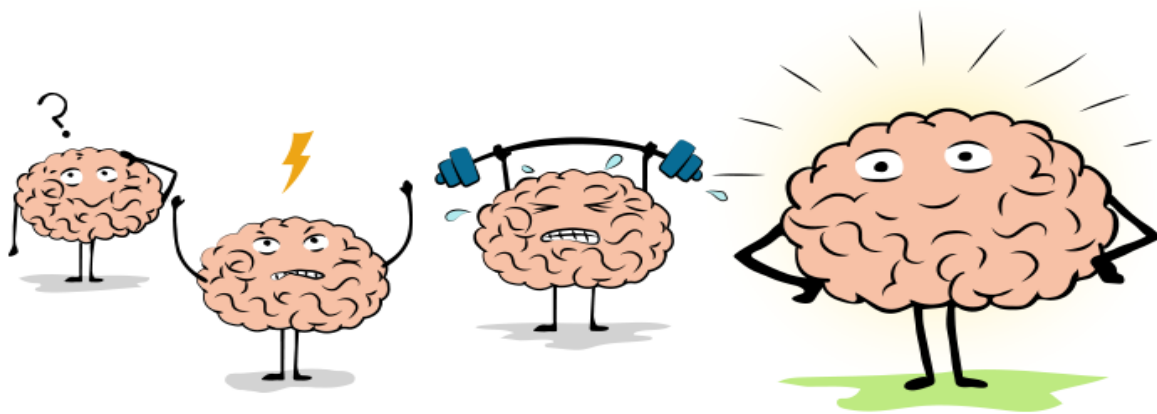
In part two, the computer program randomly allocates the students to either the treatment or the control group. The treatment group is first presented with information about research in neuroscience, which explains that the brain will grow and develop when challenged. The metaphor that the brain is like a muscle, which grows and develops when exposed to new things, are used several times, to reinforce the intervention's main message. This research is originally written by Blackwell et al (2007) and then revised by Yeager et al. (2016). It has then been adapted to the Norwegian language and culture, as part of a computer program in the U-say project created by Bettinger et al. (2018).

The intervention we have created is a modified version of the U-Say computer program. We have altered it to a one-session intervention; which makes it somewhat shorter. Also, it did not give the participants the opportunity to write down their own thoughts about certain topics, as for example how they would encourage someone to use a growth mindset to evolve their brain capacity. We also changed the content that was specifically about high-school

students to fit our target audience better. Other than that, the content and visual layout are the same as the original computer program.

The intervention presents the content by text and illustrations, and is shown on several screens. Figure 4 shows an example of an illustration from the treatment group. The information from the article about research in neuroscience is followed by quotes from scientists and celebrities endorsing the mindset. Explaining, once again, about the brain's ability to grow stronger when facing challenges, which leads to the development of skills and possibilities, both now and later in life. Lastly, the treated group is exposed to strategies for handling difficult problems, like asking for help, try to solve problems with a different approach and that they have access to resources that could help them.

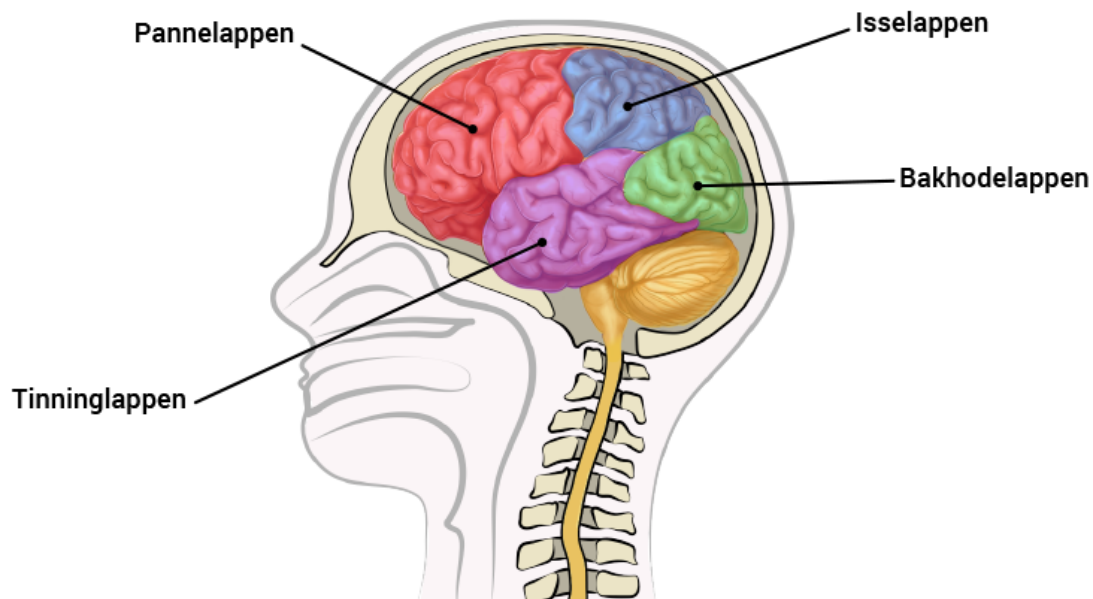
Figure 4: Picture from one of the intervention screens for the treatment group



Source: U-say; A computer program by Bettinger et al. (2018).

The students randomized into the control group are presented with basic information on how the brain functions and information about what the different parts of the brain do. For example, that the frontal lobe is responsible for our personality, and is also the part where you make decisions and plans. The control group is also told stories of how we have learned about the brain throughout the centuries and that there still needs more research to fully understand how the brain works. The information given in the control group is presented in a similar format as the treated group, with text and illustrations over several screens, as seen in figure 5. The two versions, treatment and control, are presented in similar formats to avoid the participants noticing the different information given and get confused, compare or talk about the information they were given.

Figure 5: Picture from one of the screens in the control group



Source: U-say; A computer program by Bettinger et al. (2018).

4.1.3 Effort Task

The third part consists of a real-effort task of programming a calculator. This task is made to measure the participant's performance to compare the treated and control group's performance. The effort task is developed by us, and is our contribution to this experiment. The programming task has two parts; first, the participants will read a two-page instruction that describes step-by-step how to program a simple functioning calculator using Java-programming language. Second, the participants are asked to answer ten multiple-choice questions with three choice alternatives regarding the information they just learned.

The instruction explains how to program a simple functioning calculator from start to finish by describing step by step what to do, and how the different codes and commands are written. For example, that every command line has to end with “ ; “, or how to change the font to Tahoma. bold and size 20, respectively, the command for this is “btn0.setFont (new font (“Tahoma”, Font. BOLD, 20));”. Table 6 shows an example on some programming codes.

Figure 6: Example from programming a button

```
JButton btn0 = new JButton( "0" );  
btn0.setFont(new Font("Tahoma", Font.BOLD, 20)) ;  
btn0.setBounds (10, 166, 59, 50) ;  
frame.getContentPane().add(btn0) ;
```

Notes: Picture used in the instruction for how to program a calculator; the figure shows an example of how coding of one of the buttons on the calculator looks like, and how to write the code for font correctly.

The multiple-choice questions ask about how these codes and commands are written and how they work. For example, by asking which sign every command line needs at the end to work, or which code is used to define a variable and so on. We chose to measure how well each participant did by using multiple-choice questions for simplicity, and because according to Lister et al. (2009) minimal explaining and competence is required before the initial competence to write code will emerge. The instructions and multiple-choice questions are shown in the appendix.

The performance given in the task is measured by measuring how long each participant used to read the instructions, and how much time each participant spent on each multiple-choice question. We put a 45 seconds timer on each question, which was also viewed to the participants, to raise the level of difficulty of the task. When the 45 seconds was up the participants were automatically moved to the next question. The information about the timer was given before they read the programming instructions.

Measuring the time spent on the programming task could show that some of the students might have rushed through both the instructions and the questions, and not spent a sufficient amount of time actually trying to get the answers right. We would imagine that the students with more of a growth mindset managed to stay focused for a longer period and have more perseverance than those with a fixed mindset, and therefore spend more time on the task. However, it could also indicate that because the students with a growth mindset can stay focused, they spend less time and can move faster through both the instructions and the multiple choice questions. We can therefore not conclude or be certain that time usage indicates more of a growth or fixed mindset. The time spent on the different parts of the task

does not necessarily give us an accurate indicator if they actually tried their best or just guessed on the multiple choice questions, but it should be able to give us an indicator if they read the instructions and tried to answer the questions correct, or just rushed through it.

4.1.4 Mindset measures and Demographic information

In the fourth and final part of the experiment, to measure post-intervention mindset, the participants are asked to rate the same four mindset statements as in part one. In addition, they are asked to answer demographics like age, gender, parent's education levels, if they are enrolled in a bachelor or master's degree and the field of study they have chosen.

5. Sample and Procedure

5.1 Sample

The participants in our experiment are college students at the University of Stavanger, Norway. Our sample is of convenience, as we are students at the university, which made recruitment more time-efficient. We also chose this sample because it has previously been shown that growth mindset interventions are dependent on matching the target population (Dweck and Yeager, 2019). The interventions have usually been tested on high-school students and younger adolescents (Bettinger, Mari, Dweck and Yeager, 2019). We therefore wanted to see if a growth mindset intervention would have similar effects on university students, as well.

We recruited participants by contacting various faculties at the university, asking them to share our invitation with their students. Our invitation contained information about the experiment, where and when it was being held and a link/QR-code to the sign-up form. At first we only wanted "Social studies" students to participate in the experiment, to reduce the likelihood they knew anything about programming. Then, mid-recruitment process we decided to open up for students with more analytical subjects as well to do deeper analysis and compare the different study directions. The faculties feedback was varied, but some agreed to send out our invitation to participate by email or post it on Canvas. Canvas is a learning platform where students get all the information about their courses and other relevant information from the university. In addition we posted the invitation in various study specific Facebook groups. These groups were closed, and linked to the university, so we could be sure

only students attending the university received our invitation. We also recruited face-to-face at the universities canteens, giving the same information the others received, encouraging them to participate in the experiment.

HH UiS (The Business school at the University of Stavanger) already has established recruitment processes for recruiting students to research experiments by sending out invitation to participate by email. However, we decided not to take advantage of this opportunity because we saw that we were able to recruit enough people to our experiment with our previously mentioned methods, and also, because we only opened for these students in the mid-process of recruiting participants.

5.2 Procedure

All data collected and used in the experiment are entirely anonymous. The experiment design is chosen to comply with NSD's (Norwegian Centre for Research Data, 2018) research requirements for statutory data privacy. Because the sample is small ($n=87$), in addition to coding the experiment to be anonymous, other precautions such as categorizing age and exclude IP-addresses, are made to prevent identifications. Also, the information needed for the payouts, and sponsors reimbursement, cannot in any way be linked to the participant's answers. The experiment and payments were treated separately to ensure there was no link.

We conducted the experiment in a classroom at the University of Stavanger. The participants were asked to bring their smartphones with enough battery capacity for approximately 45 minutes. Before the experiment started, information about the experiment was given; that the experiment would be conducted in a computer program through their smartphones, which would last approximately 30-40 minutes, that their answers are completely anonymous and how the payout process after the experiment works. We also told them to work independently and not talk to each other. Lastly we emphasized that there would be a lot of information to read, so we encouraged them to take the time they needed to read and reflect on the information they were given, and to do their best as their final payout increases, in addition to the show up reward, by a fixed amount for each correct answer.

Through their smartphones, the students entered a link to their browser that transferred them to the experiment's computer program. By using the link, and not have the participants log in with a username we made sure that we weren't able to track or identify participants and their

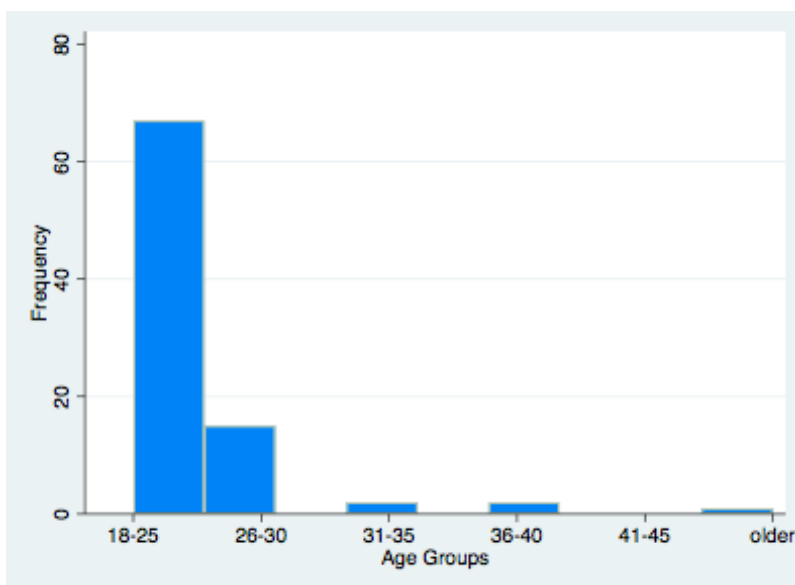
answers. The first page of the computer program was information about the experiment and for the experiment to start the participants had to give consent by pressing “I consent, start the experiment”. 90 people showed up to partake in the experiment, however, one decided not to consent to participation. The option «I do not consent, exit the experiment” was programmed to skip the experiment and transfer them to the last page of the experiment. Two students decided to withdraw before finishing part two of the experiment. Because they did not finish the intervention, or partake in the programming task we excluded their data when cleaning up the dataset, ending up with a total of 87 participants.

6. Results

6.1 Descriptive Statistics

Our experiment has 87 participants, all students at the University of Stavanger. 79% are currently enrolled in a Bachelor's degree program, while 21% are enrolled in a Master degree program. The gender distribution is 57% female. Age is categorized as 18-25, 26-30, 31-35, 36-40, 41-45 or older, but because of the skewed age distribution, age is collapsed into two groups; under and above 25 years old, with 67 and 20 participants respectively. Because the sample is a convenience sample, it is not unexpected that the majority of the participants were in the age category “under 25”. The age distribution is shown in figure 7.

Figure 7: Histogram showing the age distribution



Notes: The different age groups is 8-25, 26-30, 31-35, 36-40, 41-45 or older

Looking at the mother's education level, 10% had completed primary school as their highest level of education, 36% had finished high school, 40% had a bachelor degree, 13% had finished a master degree and only 1% had finished a PhD program. For father's' education level, 10% had finished primary school, 40% had finished high school, 25% had finished a bachelor degree, 21% had finished a master degree, and 3% had finished a PhD degree. Fathers have a mean education of 14,72 years, while mothers have a mean at 14,61 years. We checked for a correlation between father and mothers education level and found the correlation coefficient to be 0,3011, and statistically significant on a 1% level. Since they are highly correlated, we have chosen to only look at mothers education level further in our analysis.

Examining the different programs the students were studying at the university we had a substantial representation from those studying Hotel and Tourism Management by 32%. 15% study to become a teacher, 15% is enrolled at the Business school program and 10% study Media and Communication. Also, there are some students in other programs, as shown in the table below.

To simplify analysis and to be able to compare the study directions, we have divided them into two subgroups, Social studies and STEM and business studies. Social studies consist of subjects without the need for technical and analytical skills, while STEM and business are the specializations with higher demand for these subjects. We have called the second category STEM and Business studies because the Business school program and Hotel and Tourism Management is not necessarily classified as STEM studies. The reason we have chosen to place them in the same group as STEM studies is because they have some mathematical and technical subjects similar to subjects taught in STEM studies. We divided them to be able to compare the group having some technical and analytical skills against the student group without these skills.

Table 1: Distribution of the two study groups

Social studies		STEM Studies	
Teacher	15 %	Hotel and tourism	32 %
Media and Communication	10 %	Business	15 %
Cultural and Linguistics	9 %	Science and Technology	6 %
Health, Medicine, Nursing	3 %		
Social studies	3 %		
History	2 %		
Child welfare	1 %		
Sports / Physical Education	1 %		
Kindergarten teacher	1 %		

Notes: Distribution of the participant’s studies split into Social studies and STEM and Business Studies group for further analysis.

6.1.1 Balance Test

Table 2 sums up our descriptive statistics, which also includes a balance test. The four fixed mindset measures refer to the four mindset statements the participants reported in subsection 5.1.1 mindset measures. To simplify comparison, we have standardized them with a mean of zero and a standard deviation of one. A positive score on the fixed mindset measures indicates a growth mindset. The two baseline growth mindset measures are created by dividing the four mindset measures into a measure of intelligence and a measure of effort beliefs and standardizing them. People older than 25 years are an indicator for students that did not start their higher education straight out of high school but have one or more gap years. 24% are older than 25 years in the control group and 22% in the treated group. The table shows that the control group consists of 71% females, compared to 60% in the treatment group. STEM and business studies are represented with 45% and 60% in the control and treatment group, respectively.

Column 3 shows a different regression for each observable variable against treatment status, to check for differences between the treatment and control group. It shows the resulting coefficient and robust standard error in parenthesis. The mother’s education level is significantly lower in the treatment group, on a 5% level. As you can see from column 1 and 2 there is not a large difference in mothers’ education level, 15,143 years versus 14,133 years, respectively. When we asked the students about their mothers’ education level they were categorized into primary school, high school, bachelor's degree, masters degree or PhD. We have then changed this in our dataset to how many years each category represents to enrich our data. This could mean that even though there is a significant difference between the

groups, they could still belong in the same category. Finishing high school equals 13 years of education and finishing a bachelor degree equals 16 years. Both 14 and 15 years of education are within the same category, so we conclude that this difference is not important for our randomization.

There are no other coefficients that are significant, but as we have a small sample size ($n=87$), we need to take a closer look at the size of the different coefficients. We find some moderate to large differences in Fixed Mindset IT, Fixed Mindset Effort and Baseline Growth Mindset Effort, with -24%, -26% and -28% of a standard deviation, respectively. This means that the control group has a somewhat higher growth mindset on effort beliefs than the treatment group. The Mindset measures on Fixed Mindset 2 and Baseline Growth Mindset on intelligence also have some small differences, with 19,8% and 13,8% of a standard deviation, respectively. Because Baseline Fixed Mindset Effort is an average of the Fixed Mindset IT and Fixed Mindset Effort, and Baseline Growth Mindset Intelligence is an average of Fixed Mindset 1 and 2, we use the baseline measures to carefully control for this in our further analysis.

Table 2: Descriptive Statistics and Balance test

Descriptive Statistics and Balance test			
	Control	Treatment	Difference
	(1)	(2)	(3)
Fixed Mindset 1	-0,009 (0,991)	0,009 (1,019)	0,018 (0,216)
Fixed Mindset 2	-0,102 (1,112)	0,095 (0,885)	0,198 (0,216)
Fixed Mindset IT	0,126 (0,941)	-0,117 (1,049)	-0,243 (0,213)
Fixed Mindset Effort	0,134 (0,885)	-0,125 (1,092)	-0,260 (0,212)
Baseline Growth Mindset Intelligence	-0,071 (1,052)	0,067 (0,956)	0,138 (0,216)
Baseline Growth Mindset Effort	0,146 (0,911)	-0,137 (1,068)	-0,283 (0,212)
Female	0,071 (0,457)	0,6 (0,495)	-0,114 (0,102)
Older than 25	0,238 (0,431)	0,222 (0,420)	-0,016 (0,091)
STEM and business studies	0,452 (0,504)	0,6 (0,495)	0,148 (0,107)
Mothers education level	15,143 (2,055)	14,133 (2,659)	-1,009* (0,508)

Notes: *p<0,05, **p<0,01, ***p<0,1. Dependent variable listed in each row. Column 1 and 2 show the mean (and standard deviation) from the control and treatment group. Column 3 shows the estimated coefficient (and standard deviation) from different regression for each covariate against treatment status.

6.2 Correlation

Table 3 and 4 presents correlation matrices for the pre-treatment mindset measures. The numbers are Pearson correlation coefficients, which go from -1 to 1. Closer to 1 means a strong correlation, and a negative value indicates an inverse relationship (roughly, when one goes up, the other goes down). The stars indicate those that are statistically significant on a 1%, 5% and 10% level. As seen in table 3, Fixed Mindset 1 is correlated to Fixed Mindset 2, with a correlation coefficient of 0,2233, and is statistically significant on a 5% level. This is not surprising, as these mindset of intelligence statements are alike, but framed differently. Table 4 shows that Fixed Mindset IT and Fixed Mindset Effort is strongly correlated, with a correlation coefficient of 0,5788, and is statistically significant on a 1% level. This tells us that the students with a fixed mindset towards IT and computer science also have a fixed

mindset when it comes to their effort. This also applies vice versa, those who have a growth mindset and believe they can be good at IT and computer science with hard work and practice, also believe they can become better at different subjects in school if they put the effort in.

Both the correlation coefficient for Fixed Mindset 1 and 2, and for Fixed Mindset IT and Fixed Mindset Effort is above 0,20. The value of 0,20 represents the midpoint between a small to a moderate effect by Cohen (1998) standards, and we can conclude that the correlation between Fixed Mindset 1 and 2 has a small to moderate effect. The correlation between Fixed Mindset IT and Fixed Mindset Effort has a moderate to strong effect.

However, the student's mindset on intelligence did not correlate with their mindset on effort beliefs. Because there is no correlation between the mindset on intelligence and mindset on effort beliefs we have created two baseline mindset measures; one for baseline growth mindset intelligence, which are the mean of Fixed Mindset 1 and 2, and a second baseline measure which consist of the mean of the two last statements related to the participant beliefs about effort. The baselines measures have also been standardized with a mean of zero and a standard deviation of one. To justify combining the variables they have to correlate. When variables correlate it means that one statement predicts the answer of the other.

Table 3: Correlation between Pre-Treatment Mindset Measure on Intelligence

Correlation between Pre-Treatment Mindset Measures on Intelligence		
	Fixed Mindset 1	Fixed Mindset 2
Fixed Mindset 2	0.2233*	
Baseline Growth Mindset Intelligence	0,7821**	0,7821**

Notes: *p<0,05, **p<0,01, ***p<0,1. Correlation between pre-treatment measures on intelligence, included baseline growth mindset intelligence (n=87).

Table 4: Correlation between Pre-Treatment Mindset Measure on Effort Beliefs

Correlation between Pre-Treatment Mindset Measures on Effort Beliefs		
	Fixed Mindset IT	Fixed Mindset Effort
Fixed Mindset Effort	0,5788**	
Baseline Growth Mindset Effort Beliefs	0,8885**	0,8885**

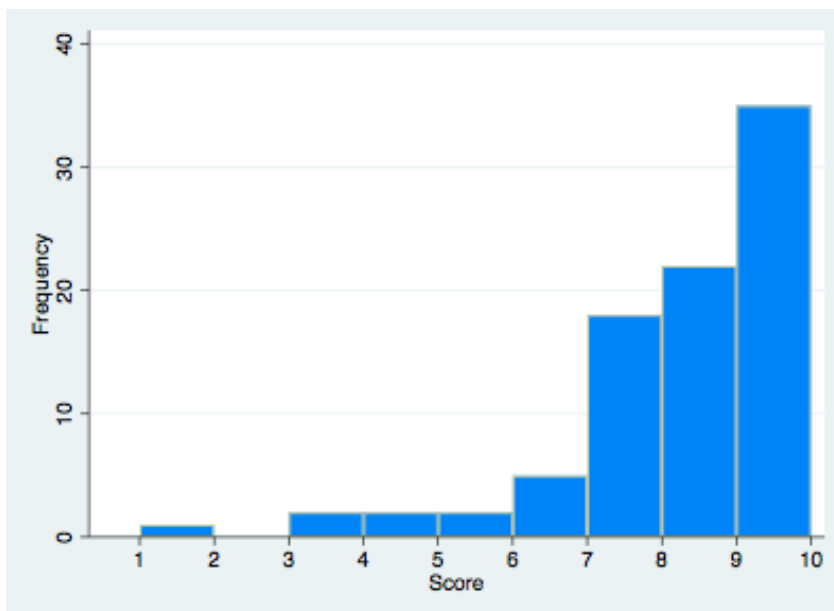
Notes: * $p < 0,05$, ** $p < 0,01$, *** $p < 0,1$. Correlation between pre-treatment measures on effort beliefs, included baseline growth mindset effort beliefs (n=87).

6.3 Validation of the Programming task

The effort task is the innovative part of our master thesis, thus previously not validated.

After the data collection and before the analysis, we “cleaned” the dataset to obtain accurate results in the analysis. This was done by going through the dataset and remove variables we did not need for our analysis, like for example meta-info and recorded date. We also removed the observations for the students that did not finish the experiment, as we did not have enough data on these to use in our analysis.

Figure 8: Histogram of distribution of Score on Programming task



Notes: Show a skewed distribution of the students score on the programming task.

We would preferably see that the student's scores on the ten multiple-choice questions in the effort task had a normal distribution. The student scores (mean 7.94 out of 10) were higher

than we anticipated, and are skewed to the right. The pilot test had a mean distribution just above the center, and because of feedback from the pilot test we changed two of the questions the participants in the pilot thought were too obvious. As the distribution in the pilot test was somewhat normal, and we changed the two questions they identified as too easy, we decided not to alter the remaining questions or add a fourth alternative answer to make it more challenging. We also debated whether to make the time limit of 45 seconds shorter, but did not want it to be too disturbing as we wished to see if there was a difference in time spent on the treated students and those in the control group. We therefore kept the time limit of 45 seconds on each question.

6.3.1 Predictors on score

We further validate our effort task by looking at predictors on score. In table 5 we examine if any of our pre-treatment variables predict the score on the programming task. Each column presents a different regression and shows the coefficients and robust standards errors in parenthesis. We investigate if any of the variables could predict the participants score on the effort task, using the score on the programming task as the dependent variable. None of the covariates are significant, and there is no significant relationship among the variables, however, the covariates indicate that it is more likely for participants to do better on the real effort task if you are female and older than 25 years old by 32% and 20%, respectively. A Social Studies student is 34 % more likely to score higher on the programming task than the STEM and business students. It is also 21% more likely that students having a baseline growth mindset of intelligence score higher on the test than students having a fixed mindset on intelligence, whereas there is a negative relationship between baseline growth mindset on effort beliefs and high score on the programming task, indicating that those having a baseline fixed mindset are 17 % more likely to score higher than those with a baseline growth mindset.

Preferably we should have had more time to validate the effort task measure, but within the limited timeframe, we had to move on to other parts of the experiment. Even though our effort task had several weaknesses, such as sample size and effort measure, we still have numerous significant findings.

Table 5: Predictors of Score on Programming task

	Predictors of Score on real-effort task						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	0,319 (0,415)						0,540 (0,447)
Older than 25		0,204 (0,412)					0,257 (0,506)
STEM and business Studies			-0,339 (0,390)				-0,200 (0,426)
Mothers Education Level				0,091 (0,095)			0,097 (0,102)
Baseline Growth Mindset Intelligence					0,206 (0,265)		0,232 (0,272)
Baseline Growth Mindset Effort						-0,174 (0,174)	-0,231 (0,189)
R-squared	0,0072	0,0023	0,0090	0,0151	0,0130	0,0093	0,0634

Notes: * $p < 0,05$, ** $p < 0,01$, *** $p < 0,01$. Dependent variable: Score. Each column presents a different regression and reports the estimated coefficient (robust standard error) for all included covariates. Sample: $n=87$

6.4 Predictors of Growth Mindset

In table 6 we examine if any of our pre-treatment variables predict a growth mindset. Each column presents a different regression and shows the coefficients and robust standard errors in parentheses.

In panel A we examine how the different variables are able to predict the participants growth mindset on intelligence, using the standardized baseline growth mindset on intelligence as dependent variable. In column 3 we see that the Social Studies students are more inclined to a growth mindset than those in the STEM and Business Studies by 47% of a standard deviation, and is significant on a 5% level. This means that a student's choice of study is a predictor of their growth mindset on intelligence. In column 5 we have added all the covariates in one regression, to control for robustness, and find it both robust and significant on a 5% level. None of the other pre-treatment covariates show a significant relationship to a growth mindset on intelligence. However, although not significant, there is an indication that males and people older than 25 are more inclined to have more of a growth mindset of intelligence by 34% and 29 % respectively.

In panel B we have used the standardized baseline growth mindset for effort beliefs as dependent variable. None of the covariates are significant, however, columns 1-3 give a strong indication that presence of growth mindset on effort beliefs seems to be more likely for participants who are female by 31% ,below the age of 25 by 27% and 25% more likely for students who are social studies students. These coefficients are small to moderate in magnitude, however, not significant.

Table 6: Predictors of a Growth Mindset

Predictors of Baseline Growth Mindset					
	Baseline Growth Mindset Intelligence				
	(1)	(2)	(3)	(4)	(5)
Panel A:					
Female	-0,342 (0,220)				-0,343 (0,224)
Older than 25		0,291 (0,252)			0,144 (0,266)
STEM and business Studies			-0,467* (0,206)		-0,479* (0,204)
Mothers Education Level				-0,0004 (0,053)	-0,01 (0,049)
R-squared	0,027	0,015	0,0549	0	0,0907
Panel B:					
	Baseline Growth Mindset Effort Beliefs				
	(1)	(2)	(3)	(4)	(5)
Female	0,314 (0,218)				0,246 (0,234)
Older than 25		-0,272 (0,234)			-0,24 (0,245)
STEM and business Studies			-0,254 (0,214)		-0,264 (0,213)
Mothers Education Level				-0,005 (0,051)	-0,012 (0,052)
R-squared	0,023	0,013	0,0163	0,0001	0,0466

Notes: *p<0,05, **p<0,01, ***p<0,1. Dependent variable listed in top row. Each column presents a different regression and reports the estimated coefficient (robust standard error) for all included covariates. Sample: n=87

6.5 Treatment Effects

6.5.1 Treatment effects on mindset

In table 7 we investigate if the intervention has affected the participants' growth mindset. We asked the participants to answer the same four mindset statements after the intervention and

programming task, as they did in part one of the experiment. To investigate this we created a post-treatment measure for growth mindset on intelligence and a post-treatment measure for growth mindset on effort beliefs the same way we created the baseline measures. These post-treatment measures have been standardized as well. In columns 1 and 2 the post-treatment measure for growth mindset on intelligence is the dependent variable. It shows the treatment effect to be 34,2% of a standard deviation increase in growth mindset on intelligence, however, not significant. When controlling for other observable variables in the regression we find that being part of the treatment group increased the growth mindset on intelligence by 31,5% of a standard deviation. This finding is significant at a 10% level.

In column three and four, we have used the post-treatment measure for growth mindset on effort beliefs as the dependent variable. It shows a treatment effect of 45,2% of a standard deviation and is significant on a 5% level. When investigating for robustness by controlling for other variables it shows a treatment effect of 62,2% of a standard deviation and is significant on a 1% level.

The findings of treatment effects on mindset are stronger for growth mindset on effort beliefs than for growth mindset on intelligence. This tells us that the students have read the information given in the intervention and that they have internalized at least some of the information about the brain being malleable and growing stronger when learning new tasks.

Table 7: Post-Treatment Growth Mindset

	Post-Treatment Growth Mindset			
	Post-Treatment Growth Mindset Intelligence		Post-treatment Growth Mindset Effort Beliefs	
	(1)	(2)	(3)	(4)
Treatment	0,342 (0,213)	0,315*** (0,172)	0,452* (0,209)	0,622** (0,176)
Female		-0,036 (0,165)		0,057 (0,181)
Older than 25		0,298*** (0,172)		-0,146 (0,203)
STEM and business Studies		-0,288*** (0,166)		0,003 (0,191)
Mothers Education Level		-0,033 (0,029)		-0,002 (0,038)
Baseline Growth Mindset Intelligence		0,521** (0,083)		-0,013 (0,079)
Baseline Growth Mindset Effort Beliefs		0,122 (0,101)		0,586** (0,091)
R-squared	0,0296	0,4297	0,0517	0,4058

Notes: *p<0,05, **p<0,01, ***p<0,1. Dependent variables listed in top row. Each column shows a different regression and reports the estimated coefficient for all included covariates (robust standard deviation) (n=87)

6.5.2 Treatment effect on real-effort task

In table 8 we have used the participants score on the programming task, to take a closer look at how treatment affected the participant's effort and performance. The table shows the coefficients and robust standard errors in parenthesis. From the table, we can see that the control group scored 0,756 points higher than the treatment group, and it is significant on a 5% level. When controlling for other observable variables it is still significant on a 5% level, and the score is 0,736 points lower for treated students than students in the control group.

When taking a closer look at the time spent reading the instructions and answering each multiple-choice questions in part 3, we see that the students in the treatment group spent less time on both reading the instructions and answering the questions. When checking for differences, as shown in table A1 in the appendix, there is only a significant difference spent on questions 3 and 4, but only on a 10% level. As there is no significant difference in reading

the instructions, and most of the questions, we might believe that there is no treatment effect on how much time the participants spent on doing the real effort task.

Table 8: Treatment Effect on Programming task

	Treatment Effect on Real-Effort task	
	Score on real-effort task	
	(1)	(2)
Treatment	-0,756*	-0,736*
	(0,377)	(0,351)
Female		0,456
		(0,427)
Older than 25		0,183
		(0,516)
Specialization		-0,11
		(0,429)
Mothers Education Level		0,064
		(0,098)
Baseline Growth Mindset Intelligence		0,269
		(0,270)
Baseline Growth Mindset Effort		-0,280
		(0,178)
R-squared	0,0445	0,1013

Notes: * $p < 0,05$, ** $p < 0,01$, *** $p < 0,1$. Dependent variable listed in top row. Each column shows a different regression and reports the estimated coefficients (robust standard error) for all covariates (n=87).

6.5.3 Treatment effect on effort, subsample analysis

In table 9 we look at how treatment has affected the score in the real-effort task and post-treatment growth mindset, for different subsamples. We split the sample into pre-treatment fixed and growth mindset on intelligence and effort beliefs, study directions and mothers level of education. As the mindset variables are standardized we split them at value zero, and those with a mindset mean above zero is categorized as having a growth mindset, while those under zero are categorized as having a fixed mindset. Mothers' education level has for this subsample been standardized the same way as baseline measures on mindset to be able to split them in low and high education.

Table 9: Treatment Effects on Score and Mindset. Subsample Analysis

	Treatment effect on effort. Subsample analysis					
	Score on multiple-choice questions		Post-treatment Growth Mindset Intelligence		Post-treatment Growth Mindset Effort Belief	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Pre-Treatment Fixed Mindset Intelligence (n=32)						
Treatment	-0,5 (0,704)	-0,511 (0,765)	0,439 (0,445)	0,419 (0,431)	0,196 (0,341)	0,197 (0,345)
Adj R-squared	-0,0162	-0,1191	-0,0008	0,1272	-0,0221	0,0266
Panel B: Pre-Treatment Growth Mindset Intelligence (n=55)						
Treatment	-0,914* (0,448)	-0,747 (0,493)	0,251 (0,168)	0,305 (0,182)	0,599* (0,270)	0,582* (0,275)
Adj R-squared	0,0554	0,0017	0,0220	-0,0011	0,0680	0,1532
Panel C: Pre-Treatment Fixed Mindset Effort Beliefs (n=60)						
Treatment	-1,111* (0,447)	-0,944* (0,454)	0,609 (0,257)	0,224 (0,250)	0,514* (0,252)	0,522*** (0,265)
Adj R-squared	0,0807	0,0918	-0,0065	0,0893	0,0511	-0,0102
Panel D: Pre-Treatment Growth Mindset Effort Beliefs (n=27)						
Treatment	-0,2 (0,686)	-0,501 (0,772)	0,742*** (0,376)	0,802*** (0,441)	0,613** (0,216)	0,617* (0,262)
Adj R-squared	-0,0365	-0,0144	0,1001	0,0469	0,2141	0,1087
Panel E: Social Studies (n=41)						
Treatment	-0,812 (0,600)	-0,809 (0,660)	0,298 (0,120)	0,245 (0,188)	0,554*** (0,316)	0,796** (0,272)
Adj R-squared	0,0203	-0,0197	0,0298	0,2642	0,0493	0,3951
Panel F: STEM and business studies (n=46)						
Treatment	-0,639 (0,501)	-0,627 (0,540)	0,547 (0,351)	0,311 (0,299)	0,391 (0,292)	0,471*** (0,263)
Adj R-squared	0,0137	-0,0595	0,0309	0,3471	0,0173	0,2579
Panel G: Mother Low Education (n=40)						
Treatment	-0,665 (0,615)	-0,678 (0,671)	0,575*** (0,288)	0,489*** (0,251)	0,361 (0,327)	0,449 (0,288)

Adj R-squared	0,0043	-0,1206	0,0172	0,3323	0,0056	0,2748
Panel H: Mother high Education						
(n=47)						
Treatment	-0,900***	-1,046***	0,153	0,224	0,464	0,757**
	(0,514)	(0,538)	(0,325)	(0,262)	(0,294)	(0,261)
Adj R-squared	0,0430	0,0819	-0,0172	0,4216	0,0313	0,3310
Control Variables included	No	Yes	No	Yes	No	Yes

Notes: *p<0,05, **p<0,01, ***p<0,1. Dependent variable listed in the top row. Each panel represents a different subsample and shows the separate regression and estimated coefficients (robust standard error) and adjusted R-square. Last row shows if the regression includes control variables. Control variables are female, above 25 years, STEM and business studies, baseline growth mindset intelligence and baseline growth mindset effort beliefs.

Panel A takes a closer look at the students with a pre-treatment fixed mindset on intelligence. Column 1 shows that among the students with a pre-treatment fixed mindset on intelligence, treated students scored 0,5 points lower than the control group. The treatment group has also increased their mindset on intelligence with 43,9% of a standard deviation, and 19,6% of a standard deviation on effort beliefs, as shown in columns 3 and 5. Column 2, 4 and 6 show the results when controlling for other observable variables. The finding on treatment effects for post-treatment growth mindset on intelligence is large in magnitude, while the effect on post-treatment growth mindset on effort is small to moderate. However, they are not significant. As seen from our sample, there are only 32 students included in the data in panel A, and when dividing a small sample (n=87) into several subsamples it becomes difficult to find significant results. When controlling for six other variables, there is almost not anyone left to compare to, and significant findings are therefore hard to get.

Panel B, column 1, shows that among those with a pre-treatment growth mindset on intelligence, treated students scored 0,914 points lower than the students in the control group. This is significant on a 5% level. In columns 3 and 5 we see that for the treated students with a pre-treatment growth mindset on intelligence the intervention increased their mindset on intelligence and effort beliefs with 25,1% and 59,9% of a standard deviation, respectively. The increase in mindset on intelligence is not significant, however, their mindset in effort beliefs is significant on a 5% level, and is still significant when controlling for observables, in column six. The sample is a bit larger in this group, n=55, but it is still very small.

In panel C we investigate the treatment effect on the real-effort task and post-treatment growth mindset on intelligence and effort beliefs for those with a pre-treatment fixed mindset

on effort beliefs. Panel C, column 1, shows the treatment effect for the students having a pre-treatment fixed mindset on effort beliefs to perform 1,111 points lower than the control group. It is also significant on a 5% level. In column 3 and 5, we see that post-treatment mindset on intelligence and effort beliefs has increased for the treated students, with 60,9% and 51,4% of a standard deviation, respectively. The increase in growth mindset on intelligence is not significant, but large in magnitude, while treatment effect on effort beliefs is both large and significant on a 5% level.

Panel D takes a closer look at the students possessing a pre-treatment growth mindset on effort beliefs, and find treated students to score only 0,2 points lower than the control group, as seen in column 1. However, they are not significant. In column 3 and 5 we look closer at how the intervention affects the treated student's growth mindset on intelligence and effort belief, and find that the treatment increases their growth mindset of intelligence and effort beliefs with 74,2% and 61,3% of a standard deviation, respectively. The changes in growth mindset are large, and are also significant on a 10% and 1% level, respectively.

The results in panel A-D, column 1, means that the treated students with a pre-intervention fixed mindset on intelligence and pre-treatment growth mindset on effort beliefs did better on the real-effort task than the treated students with a pre-treatment growth mindset on intelligence and pre-treatment fixed mindset on effort beliefs. In columns 3 and 5 we find an especially large increase in post-treatment growth mindset on intelligence and effort beliefs for treated students with a pre-treatment growth mindset on effort beliefs.

In panel E and F, we examine if the choice of study direction, Social studies or STEM and business studies, can determine students that are particularly responsive to treatment. Table 6 showed that prior to treatment, students in Social Studies exhibited more of a growth mindset on intelligence than STEM and Business students, thus we look at treatment effects splitting the sample based on study direction. We have also provided a balance test with coefficients for regressions on this subsample in appendix, table A8, which find the subsample balanced on all variables.

Even though the students in social studies had more of a pre-treatment growth mindset of intelligence it turns out that treated students in STEM and business studies did slightly better than treated students in social studies, as seen in column 1. With 0,64 and 0,81 points lower

than the control group, respectively. Taking into account that treated students with a pre-treatment growth mindset on intelligence had 0,914 points lower than the control group, and that social studies seem to be a predictor for this measure, it is not surprising that treated STEM and business students performed better on the real-effort task. However, the results are not significant.

In columns 3 and 5, in panel E, we investigate how the treated students in Social studies mindset on intelligence and effort beliefs change after the intervention, and find an increase of 29,8% and 55,4% of a standard deviation, respectively. The increase in treated Social studies students' mindset on effort belief is large, and also significant on a 10% level. When controlling for other observables it is significant on a 1% level and even larger in magnitude, with 79,6% of a standard deviation. Panel F shows that there is also an increase in mindset on intelligence and effort belief for the treated STEM and Business students after the intervention, with 54,7% and 39,1%, respectively. The results for this study category is not significant, except for in column 6, when controlling for other observables in change in mindset on effort beliefs. The results show an increase of 47,1% of a standard deviation, respectively, and are significant on a 10% level.

In panel G and H, we examine treatment effects on performance in the real-effort task and change in mindset after the intervention based on the mother's education level (high vs low). To make this possible we have standardized mothers' education level with a mean of zero and a standard deviation of 1. We have then characterized mothers with low education to be those below the mean. We have also provided a balance test with coefficients for regressions on this subsample in appendix A, table A9, that finds the subsample well balanced on all variables.

In panel G, column 1, the treated students with less educated mothers, scored 0,665 points lower than those in the control group. The treated students, in panel H, with higher educated mothers scored even lower, with 0,9 points less than the control group. However, it is only for the higher educated mothers it is significant, and only on a 10% level. When controlling for other variables they perform even lower, with 1,046 points lower than those in the control group. Mother's' education level is widely used as a predictor for children's performance in school and higher education, so this was not an expected finding.

When looking closer at the effect of treatment for treated students mindset on intelligence in panel G, column 3, we find a large and significant increase in growth mindset on intelligence for treated students with low educated mothers, with 57,5% of a standard deviation, respectively. The treatment effect is also at least moderate on their increase in growth mindset on effort belief with 36,1% of a standard deviation, however not significant. For the treated students, who have mothers with higher education, in panel H, column 3, the effect of the intervention on their mindset on intelligence is small, with an increase of 15,3% of a standard deviation, but not significant. In column 5, we see that the intervention increases the treated students with higher educated mothers growth mindset on effort beliefs with 46,4% of a standard deviation, and when investigating for robustness by controlling for other variables the effect is 75,7% of a standard deviation and significant on a 1% level.

7. Discussion

7.1 Treatment effects on Mindset

When examining how treatment changes the participants' mindset we found a significant effect on both the participants' mindset on intelligence and effort beliefs in table 7. When we investigate for robustness by controlling for other variables we find an increase of 31,5% of a standard deviation in the treated student's mindset on intelligence, which is also significant on a 10% level. The largest effect, however, was found on the treated participants change in effort beliefs when controlling for other observables, with an increase of 62,2% of a standard deviation, and is significant on a 1% level. This confirms our hypothesis 1; that the intervention alters the treated participant's mindset to more of a growth mindset compared to their mindset pre-intervention.

For further analysis, we divided them into different subsamples of pre-intervention fixed and growth mindset on intelligence and effort beliefs, and also by study direction and mother's education level.

As seen in table 9, panel A-B, column 3, the treated student's growth mindset on intelligence increased post-treatment for both those with a pre-treatment fixed and growth mindset on intelligence, with 43,9% and 25,1% of a standard deviation, respectively. In panel C and D, column 3, we found the treated students with a pre-treatment fixed and growth mindset on effort beliefs to increase their post-treatment growth mindset on intelligence with 60,9% and

74,2% of a standard deviation, respectively. However, it is only significant on a 10% lever for treated students with a pre-treatment growth mindset on effort beliefs.

We have also examined how treatment affected the participants' mindset on effort beliefs in table 9, panel A-D, column 5, and find large effects on all subsamples. The treated students with a pre-treatment fixed mindset on intelligence only had a small increase in their mindset on effort beliefs post-intervention, with 19,6% of a standard deviation, but are not significant. Treated students with a pre-treatment growth mindset on intelligence and a pre-treatment fixed mindset on effort beliefs increased their mindset on effort beliefs with 59,9% and 51,4% of a standard deviation post-treatment. These are significant on a 5% level. However, the largest effect of treatment was found for the treated students with a pre-treatment growth mindset on effort beliefs, with 61,3% of a standard deviation, and is significant on a 1% level. This is in line with findings in other studies, as for example Blackwell et al (2007) who found that an eight-week intervention influenced low-performing students belief about intelligence and math. In Blackwell et al., (2007) experiment the participants' belief on effort was reflected in their beliefs about their abilities in math.

Table 9, panel E-F, column 3, shows that both Social and STEM and Business students increased the treated participant's mindset on intelligence with moderate to large effects, with an increase of 29,8% and 54,7% of a standard, respectively. In column 5 we found an increase in a growth mindset on effort beliefs for both Social and STEM and business students, with 55,4% and 39,1% of a standard deviation, respectively. However, it is only significant for Social students, on a 10% level.

In panel G-H, column 3, found a large increase in the treated student's mindset on intelligence for those who have mothers with low education, with 57,5% of a standard deviation, and a small effect for those who have mothers with higher education, with an increase of 15,3% of a standard deviation. It is only significant for mothers with low education, on a 10% level. We also found an increase in a growth mindset on effort beliefs post-treatment in column 5 for mothers with low and high education, with 36,1% and 46,4% of a standard deviation, respectively. These are large in magnitude but are not significant. Although the results are moderate to large in magnitude, it is difficult to find significant results with a small sample size like in our subsamples.

When looking at the students' pre-treatment growth mindset on intelligence in table A3, the students in Social studies had more of a growth mindset than those in STEM and business studies prior to the intervention, with 30 against 25, respectively. Checking their mindsets on intelligence after the treatment, in table A5, students in social studies went from 30 to 34 having a growth mindset, while STEM and business studies also have slightly more of a growth mindset on intelligence post-treatment, with 25 changing to 29, respectively.

On the pre-intervention growth mindset on effort beliefs, in table A4, Social and STEM and business students do not differ as much in their mindset, with 15 and 12 having a growth mindset, respectively. However, we can see that of the total 87 participants, 60 of them had a fixed mindset on effort beliefs prior to the intervention. This has changed to only 44 having a fixed mindset on effort beliefs post-treatment, as shown in table A6. Students in Social studies have gone from 15 to 20 having a growth mindset on effort beliefs, while STEM and business studies students have changed from 12 to 23 post-treatment. STEM and business students have actually changed their mindset about beliefs of effort more than the students in Social studies.

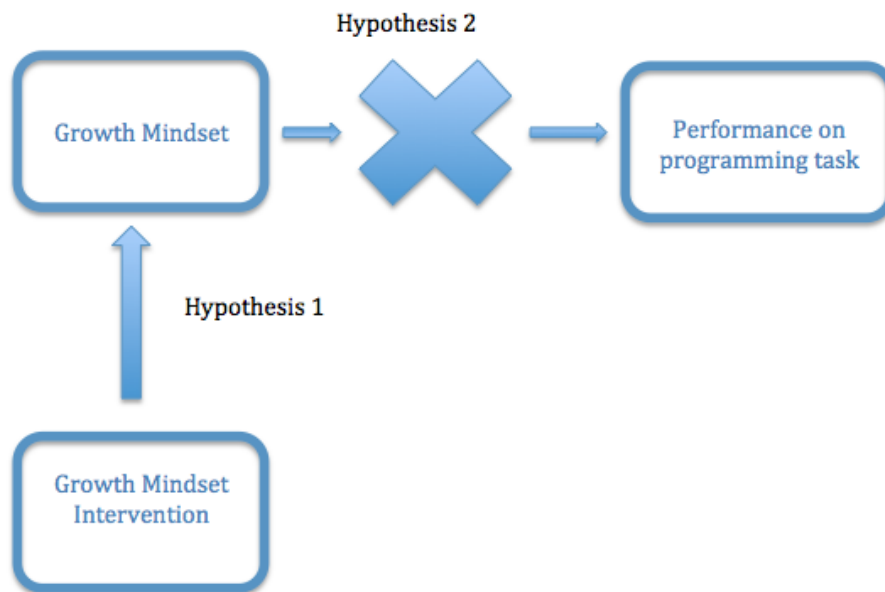
These results are the same as in our subsample analysis indicating that the participants' had more of a growth mindset on intelligence prior to the intervention and that the intervention changes their mindset on effort beliefs significantly. These findings are also consistent with findings in previous studies, as for example the study done by Bettinger et al., (2018), who found that the treatment increased the Growth Mindset score by 56% of a standard deviation. Blackwell et al (2007) also found their treated participants to endorse a growth mindset more strongly after the intervention.

The largest increase in growth mindset post-treatment is found in growth mindset on effort beliefs for students with pre-treatment growth mindset of intelligence and effort beliefs. It is interesting that the increase in a growth mindset of effort beliefs is larger for the treated students who already possess a growth mindset pre-treatment, but at the same time it makes sense, as these are the students already paying the most attention to what they are presented in the intervention.

7.2 Treatment effects on Programming task

In our experiment, the students in the control group had higher scores on the programming task than the treated students (shown in table 8) with 0,756 points. It is also significant on a 5% level. This was an unexpected result and does not support our hypothesis 2; that treated participants will perform better than the control group on the real-effort task of programming.

Figure 9: Altered figure of hypothesis 2



Notes: Figure showing that our results does not support our hypothesis 2; that a growth mindset increases performance on the programming task.

There is usually a strong link between a growth mindset and performance, and most previous studies on growth mindset interventions find that a growth mindset intervention increases the treated participant's effort, performance and willingness to take risks (Dweck and Yeager, 2019; Blackwell et al., 2019; Bettinger et al. 2018). Bettinger et al. (2018) found a large treatment effect on students with a pre-treatment low GPA, but no significant effect for those with a pre-treatment high GPA. Dweck and Yeager (2019) also found that a growth mindset intervention increased the GPA for lower-achieving students and that those with a pre-treatment high GPA benefited in other ways as for example being more willing to take on challenges. Improved academic results most often appear for students at higher risk at underperforming, and those with lower grades before the intervention.

Nevertheless, there is a study done by L. Brougham and S. Kashybeck-West (2018) that showed a slightly negative change in GPA for those exposed to the intervention, while the

GPA for the control groups increased over time. Results from other studies have also shown that the intervention affects mindset, with only a modest increase in academic performance (Dweck and Yeager, 2019).

To examine the results further we looked at different subsamples, and the participants' performance on the effort task in table 9, and found that all treated participants had a lower score on the effort task than the control group. We can see that among the treated students with a pre-treatment fixed mindset on effort beliefs and pre-treatment growth mindset on intelligence, and also the treated students who have mothers with high education mainly drive the negative result on the real-effort task, by getting a score that is 1,111, 0,914 and 0,9 points lower than the control group, respectively. The treated students with a pre-treatment growth mindset on effort beliefs and pre-treatment fixed mindset on intelligence also have a negative score, but only with 0,2 points and 0,5 points lower than the control group, however, these are not significant.

We find it interesting that the treated students with a pre-treatment fixed mindset on effort beliefs is the group who have the lesser performance of all subsamples, and might indicate that since the programming task is immediately after the intervention, they did not have time to internalize and reflect on the information from the intervention before the task was completed. The post-treatment growth mindset measures show that the treated students do in fact endorse more of a growth mindset post-treatment, but we are not able to see if they reflect on this before they answer the mindset statements for the second time. They also had a time limit on 45 seconds on each question, which might affect their ability to think strategically. Another explanation is that a growth mindset does not matter for performance in programming. However, as most participants scored well on the test, with a mean score of 7,94, it seems as most people could have managed our task well, regardless of mindset. Because there are several weaknesses in our validation of the effort task there is a need for further research to determine whether a better test of performance in programming or by eliminating the weaknesses, could change the results.

When looking at students in both the treatment and control group, the STEM and Business studies students perform 0,339 points lower than Social studies students. However, when examining only the treated groups within the different study directions in table 9, panel E-F, we see that the treated STEM and Business studies students perform better than treated Social

studies students do, with 0,639 and 0,812 points lower than the students in the control group, respectively. This means that our assumption that STEM and Business studies students would perform better on the effort task of programming is not confirmed, but within the treated groups, they perform better than Social studies students.

It appears that our growth mindset intervention has a positive effect on growth mindset, but a negative effect on performance on the programming task. Because the intervention has been validated numerous times (Blackwell et al., 2007; Bettinger et al., 2018; Dweck & Yeager, 2019), the effort task's weaknesses, such as the task difficulty level and additional monetary reward on correctly answered questions, may be the explanation for this result. Our experiment does also not measure the students' grades or performance at school pre-intervention, which means that we are not able to see if the treated students in our experiment already are high-performers pre-intervention.

In our effort task, the variation of scores was small, and most of the participant's scores were high on the multiple-choice questions (out of 87 participants 22, 16 and 19 students scored 8, 9 and 10, respectively, out of 10). This indicates that the level of difficulty on the task was not high enough; hence, the participants were possibly not sufficiently challenged on their performance. We are also not able to measure how hard each participant tried, hence their effort, because it only tells us their final score.

We have looked at the time spent on the effort task, and if there is any difference between the treated students and control group (Results listed in table A1). As mentioned, the treated students only spent a significantly shorter time on multiple-choice questions three and four. Taking a closer look at which questions the treated students scored better or worse at than the control group, and if there are any significant differences on any of them, the only question with a significant difference for treated and control students is question number ten. The treated students scored 0,267 points lower than the control students on this question. The results and balance test are listed in table A7. Considering that there was a significant difference in how much time treated and control students spent on questions three and four, we also wanted to see the outcome of the result on these questions. As table A7 show, the treated students did 0,028 points better than control students on question three, which might indicate that they managed to stay focused for a longer period of time than the control students, hence, needed lesser time to get the answer right. Looking at question four, the

treated students had 0,058 points lower than the control group, contradicting the theory of how time spent predicts the effort put in to answer the question correctly. We are therefore not able to conclude if time-use predicts effort.

Some of the key factors for people possessing a growth mindset are to have good strategies for solving problems as for example seek guidance and mentorship, don't fear new challenges, use access to resources, and try different approaches to solve different tasks (Dweck and Yeager, 2019). Another issue with our effort task is that in our experiment, the students had to work independently, and not use any form for help other than the two pages of instructions. The students did therefore not get to use any of the key factors and had to rely on the skills and strategies they had before doing the task. We also paid the students in both treatment and control group an additional 10 NOK on each correctly answered question in the programming task, which could have made both groups more willing to take on new challenges and not be as afraid of trying something new. It, therefore, would have been interesting to see if allowing for the key factors of a growth mindset would have changed the outcome, as we have found that treated students, in fact, change their mindset towards more of a growth mindset.

7.3 Other Interesting Findings

7.3.1 Correlation

The correlation between the mindset on intelligence and effort beliefs are normally very strong. Dweck proposed that mindset organize everything into a meaning system, meaning that when you have a fixed mindset this will take on other important factors as a consequence of that (Dweck & Yeager, 2019). For example, if you have a fixed mindset on effort beliefs you might not be willing to put in enough effort to improve in a task, and will therefore not reach your full potential. This will also affect how you deal with setbacks, and determine how fast you give up trying to improve. Blackwell et al. (2007) and Bettinger et al. (2018) also found that a growth mindset on intelligence correlated with both effort beliefs and helpless responses to failure.

In our experiment, we found no correlation between the participants' mindset on intelligence and their mindset on effort beliefs. However, the correlation between the two statements on effort beliefs is strong with a coefficient of 0,5788 and significant on a 1% level. The

correlation coefficient between the statements measuring the mindset of intelligence is 0,2233, and significant on a 5% level. The statements we used to measure mindset on intelligence have been used and validated in numerous studies, and have previously been adapted to the Norwegian language and context by Bettinger et al. (2018). The statements we used to measure the mindset of effort beliefs were used by Bettinger et al. (2018), but we altered one of them slightly. Bettinger et al. (2018) wanted to examine their participants' mindset on mathematics, while we changed it to computer science and IT to fit our experiment better. The phrasing of the question was still the same, but the topic we wanted to investigate was different. We also changed how large the scale of agreeing or disagreeing was, as we only had four options from agree to disagree. Previous studies have had six or seven choices in their scale (Bettinger et al. 2018; Blackwell et al. 2007).

There could be multiple reasons for our results of the mindset of intelligence correlating with the mindset of effort beliefs. As Yeager and Walton (2011) explain, even subtle changes in context or phrasing may prevent replication. As seen in table A3 and A4, 55 participants out of 87 had a pre-intervention growth mindset on intelligence, while only 27 had a growth mindset on effort beliefs. This shows that they generally have a much more fixed mindset towards effort beliefs than intelligence before the growth mindset intervention. Even though the change in one of the statements measuring mindset on effort beliefs was small, it could still alter the recipients understanding. The narrowing of options on how much a participant agrees or disagrees with the statements could also be the reason for the different results. This may have led the participant to imply a stronger belief on how much they agree or disagree on the statements that they would if the scale had more options.

When checking for correlation between the mindset measures after treatment, in table A2, we see that after the intervention it is only Fixed Mindset 2 and Fixed Mindset on effort that don't correlate. Before treatment Fixed Mindset 1 and 2, did not correlate with either of the effort beliefs. This indicates that the intervention has changed the treated students' to having a more consistent mindset across intelligence and effort beliefs.

In hindsight, we should have spent more time carefully validating the statement on their belief about computer science and IT, and also, how wide the scale of agreeing or disagreeing should have been. However, with the limited timeline available for writing a master thesis we did not have time to do this in a good enough way. There is therefore a need to further

investigate what is the exact reason for the missing correlation between mindset on intelligence and effort beliefs

7.3.2 Predictors of Growth Mindset

Basing our sample on convenience, we assume that most participants will exhibit more of a growth mindset than the general population. When students choose to enroll at university, it indicates that they, to some point, are interested in learning, thus believe in their abilities to learn and develop their skills. As a result, the students should have some level of willingness to put effort into schoolwork and exams to pass their classes. This sample description fits with Dweck and Yeager's (2019) description of a growth mindset; people with growth mindsets believe in their intelligence and seek challenges to develop their abilities further.

As shown in table 6, panel A, students choosing Social studies are a predictor for growth mindset on intelligence, with 46,7% and is significant on a 5% level. There are also other small to moderate indicators that males and participants over the age of 25 have more of a growth mindset on intelligence, with 34,2% and 29,1%, respectively. They are however not significant. Table A3 in the appendix also shows that students choosing social studies have more of a growth mindset on intelligence pre-intervention than those in STEM and Business studies, 30 to 25, respectively. This means that students' choice of study direction is a predictor of their growth mindset on intelligence. Bettinger et al. (2018) also found that study direction is a predictor for mindset and that the presence of a growth mindset is more likely among students who choose academic and not vocational track, and for those with a higher GPA. Students on the vocational track generally also have lower credentials. As we only have university students in our sample, all being on the academic track, it is interesting that we found a difference in mindset on the different directions within academics. It would be interesting to further investigate why students in social studies seem to be a predictor for a growth mindset on intelligence, and if our mindset is a predictor, for which type of study we choose.

However, as seen in table 6, panel B, there are no significant predictors for a growth mindset on effort beliefs. However, with a small sample size like ours (n=87) we still need to notice that there are some small to moderate indicators. Females, those under the age of 25 and social studies students exhibit more of a growth mindset on effort beliefs, with 31,4%, 27,2%,

and 25,4%, respectively. Table A4 in the appendix also shows that very few students have a growth mindset on effort beliefs pre-intervention, with only 15 in social studies and 12 in STEM and business studies, respectively.

Based on the difficulty of the two study directions, in which STEM and Business studies require more technical and analytical skills, the assumption would be that the STEM and Business studies students would have more of a growth mindset. When choosing this direction they welcome the challenge of learning more complex and intricate theories, more than the Social studies students. Our findings that Social studies students exhibit more of a growth mindset on intelligence pre-intervention than STEM and Business Students, contradict this assumption and is surprising. This might be explained by Social studies students facing less difficult challenges than the students in STEM and Business studies (Dweck and Yeager, 2019). As reported by Blackwell et al (2007) the challenge must be sufficient to trigger the patterns related to the theory of intelligence and effort beliefs, and it might indicate that STEM and business studies students are more often exposed to challenges they find difficult, hence why they have more of a fixed mindset pre-intervention.

7.4 Experimental Weaknesses

Throughout the experiment, we have become aware of some weaknesses with our experimental design. Some of the weaknesses are limited by scope, while others are matters we could or should have done differently. Preferably, we should have been able to run several pilot tests of the real-effort task with more participants, but because of the time limit, we only had one pilot test with 10 participants. This raises a concern about the difficulty level of the task, and in retrospect, we should have made some of the questions more difficult. A more difficult programming task would have generated a lower mean score and a normal distribution, and also would have made it possible for us to have a larger sample.

The sample is constrained by the budget. Our budget allowed for a sample size of 80-100 participants, which is a decent size for a master thesis. However, a larger sample size makes it possible for more in-depth analyses and it could be easier to find significant results. Also, our sample size limits the possibilities for subsample analysis remarkably.

Ideally, the experiment should have been conducted in a more diverse population. Measuring mindset pre- and post-intervention could then yield more interesting results for example when

it comes to age and experience. Do older people have more of growth or fixed mindset than people in their twenties? How will the intervention affect their performance and mindset? Is there a difference in mindsets based on years of working experience? How will this be affected by the intervention and task?

One would think that the intervention would have more impact if executed over several sessions, as more sessions allow the participants more time to think about what they were introduced to in the experiment. However, DeBacker et al., (2018) findings suggest that a one-shot growth mindset intervention also works well. We chose to have only one session, partly because of time constraints and because it would be difficult to get the same participants to commit to several sessions. But mostly, we wanted to test if one session would be “enough” to create a significant change in mindset and performance. It could also be interesting to see if, going over several sessions, the intervention in combination with learning strategies on how to manage the task of our choosing would get more significant results.

Another concern is that we used time spent reading the instructions on how to program a calculator as measurements for effort. We also looked at how long the participants used to answer each question, the total score and how many answers they did not complete (because when the timer for each question hit 45 seconds, they were automatically forced onto the next question). In hindsight, we could have had more time to find the optimal time given for each question, as it seems as 45 seconds might not have been strict enough for most of the participants, as very few ran out of time. However, if the task would have been more difficult, 45 seconds could have been sufficient. We have realized that this might not be the best measure to test effort because, as mentioned, the score on the task only tell how well they did, not how hard they actually tried. A better measurement for effort could, for example, be a challenging task in which the number of attempts before giving up was measured.

One of the reasons that people are afraid or less willing to try new things is their fear of not being able to manage the new task, not being good at it or revealing their weaknesses. They, therefore, dread new challenges and avoid them. Our fear of the students being afraid to try our real-effort task of programming led us to offer an additional monetary reward on each correctly answered question, to ensure that we got enough participants to our experiment and

that they would try their best on the task. In hindsight, we see that this may have contaminated the treatment effect, as it may have led also the control group to be more willing to try a challenging task they had no prior knowledge about than they normally would have. Our sample is of convenience and is based on students. Students are often in need of money, and when offering them additional pay to do well on the effort task, they could have given a higher effort, and been less afraid to try our programming task only because they needed or wanted the extra money.

8. Conclusion

We have investigated if a one-session growth mindset intervention on university students affects their mindset, and their performance on a real-effort programming task they have no prior knowledge about. Further, the effort task created is highly relevant in today's constantly changing labor market in which technology becomes more and more important, and the demand for people with a skill set in computer science and programming is highly demanded.

The treatment effects on mindset are present and positive, and in line with the first hypothesis, that predicted that a one-session intervention would increase the treated participant's growth mindset post-intervention. The presence of a growth mindset was higher for the mindset of intelligence than effort beliefs pre-intervention, especially for Social studies students. However, the growth mindset intervention had a positive effect on all subsamples and increased their growth mindset on both intelligence and effort beliefs. The largest treatment effect is found to be on the mindset of effort beliefs, and also for the treated students with a pre-treatment growth mindset on both intelligence and effort beliefs.

Our results on the programming task do not support our second hypothesis, nor other research on growth mindset intervention and effort tasks. Our hypothesis; that the treated participants would perform better on the programming task is not supported, as the students in the control group scored higher on the real effort task, with 0,756 points, respectively. Previous research has shown a strong link between mindset and performance; however, it appears to be a negative link between mindset and performance in our experiment.

There are several weaknesses with our programming task, as for example weak validation of the effort task, the additional monetary reward on correctly answered questions, and that they weren't able to use growth mindset strategies to solve the task. We tested the participants on something new and difficult that they had no prior knowledge of, hence being able to use strategies to solve the task could have helped them make use of what they learned in the intervention. There is a need for further research to determine why the link between mindset and performance is not found in our experiment, and if a growth mindset can increase performance in programming.

References

- Bettinger, E., Ludvigsen, S., Rege, M., Solli, I. F., Yeager, D. (2018). Increasing perseverance in math: Evidence from a field experiment in Norway, *Journal of Economic Behavior & Organization*, Vol 146, 1-15. <https://doi.org/10.1016/j.jebo.2017.11.032>
- Blackwell, L.S., Trzesniewski, K.H., & Dweck, C.S. (2007). Implicit theories of intelligence predict achievement across an adolescent transition: a longitudinal study and an intervention. *Child development*, 78 1, 246-63. DOI:10.1177/2156759X18764934
- Brougham, L., & Kashubeck-West, S. (2017). Impact of a Growth Mindset Intervention on Academic Performance of Students at Two Urban High Schools. *Professional School Counseling*. <https://doi.org/10.1177/2156759X18764934>
- Burnette, J.L., O'Boyle, E.H., Vaneppps, E.M., Pollack, J.M., & Finkel, E.J. (2013). Mind-sets matter: a meta-analytic review of implicit theories and self-regulation. *Psychological bulletin*, 139 3, 655-701 .DOI:10.1037/a0029531
- Chavez, D. (2010). TECH SAVVY. *Risk Management*, 57(5), 26-29.
- Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Hillsdale, NJ: Erlbaum.
- Cutts, Q., Cutts, E., Draper, S., O'Donnell, P. & Saffrey, P. (2010). Manipulating Mindset to Positively Influence Introductory Programming Performance. *Proceedings of the 41st ACM Technical Symposium on Computer Science Education* (p./pp. 431--435), New York, NY: ACM. DOI:10.1145/1734263.1734409
- DeBacker, T. K., Heddy, B. C., Kershner, J. L., Crowson, H. M., Looney, K., & Goldman, J. A. (2018) Effects of a one-shot growth mindset intervention on beliefs about intelligence and achievement goals. *Educational Psychology*, 38:6, 711-733, DOI: 10.1080/01443410.2018.1426833
- Dweck, C. S., & Yeager, D. S. (2019). Mindsets: A View From Two Eras. *Perspectives on Psychological Science*, 14(3), 481–496. <https://doi.org/10.1177/1745691618804166>
- Dweck, Carol S. (2009). Mindsets: Developing talent through a growth mindset. *Olympic Coach Magazine - Team USA*, 4-7.
- Heslin, P.A., Latham, G.P., & Vandewalle, D. (2005). The effect of implicit person theory on performance appraisals. *The Journal of applied psychology*, 90 (5), 842-56 . DOI:10.1037/0021-9010.90.5.842
- Kaasa, Cato. pwc.no. 2016. <https://www.pwc.no/no/teknologi-omstilling.html> (accessed 02.2019).
- Kafai, Y. B., and Burke, Q. (2014). *Connected Code: Why Children Need to Learn*

- Programming. The John D. and Catherine T. MacArthur Foundation Series on Digital Media and Learning. The MIT Press (July 11, 2014)
- Lazear, E. P., & Gibbs, M. (2014). *Personnel Economics in Practice*. New Jersey: John Wiley & Sons.
- Loksa, D., Ko, A.J., Jernigan, W., Oleson, A., Mendez, C.J., & Burnett, M.M. (2016). Programming, Problem Solving, and Self-Awareness: Effects of Explicit Guidance. CHI. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems (CHI '16)*. ACM, New York, NY, USA, 1449-1461.
DOI:10.1145/2858036.2858252
- Lister, R., Fidge, C. & Teague, D. (2009). Further evidence of a relationship between explaining, tracing and writing skills in introductory programming. *SIGCSE Bull.* 41, 3 (July 2009), 161-165. DOI: <https://doi.org/10.1145/1595496.1562930>
- Møller, Aage R (2009) *The malleable brain: benefits and harm from plasticity of the brain*. Nova Science Publishers; 1 edition (November 25, 2009)
- National Research Council. 2012. *Education for Life and Work: Developing Transferable Knowledge and Skills in the 21st Century*. Washington, DC: The National Academies Press. <https://doi.org/10.17226/13398>.
- Norwegian Centre for Research Data (2018). NSD - Norwegian Centre for Research Data. Retrieved from <https://nsd.no/nsd/english/>
- Raytheon Company. (2012). *Math Relevance to U.S. Middle School Students: A Survey* Commissioned by Raytheon Company.
- Rege, M., Hanselman, R., Solli, I, S., Dweck, C. S., Walton, G., Ludvigsen, S., Bettinger, E, Hooper, S. Y, Hinojosa, C., Muller, C., Ferguson, R., Schneider, B., Duckworth, A. & Yeager, D. (2018). *How Can We Inspire Nations of Learners? Evidence from Growth Mindset Interventions Conducted in Two Centuries*. Working paper
- Schoeman, M., Gelderblom, H. & Muller, H. (2013) *Investigating the Effect of Program Visualization on Introductory Programming in a Distance Learning Environment*, *African Journal of Research in Mathematics, Science and Technology Education*, 17:1-2, 139-151, DOI: 10.1080/10288457.2013.828408
- Van Merriënboer, J. J. G., & Krammer, H. P. M. (1987). Instructional strategies and tactics of or the design of introductory computer programming courses in high school. *Instructional science*, 16(3), 251-285. <https://doi.org/10.1007/BF00120253>

- Yeager, S. D. & Dweck, S. C.(2012). Mindsets That Promote Resilience: When Students Believe That Personal Characteristics Can Be Developed. *Educational psychologist*, 47(4), 302–314. DOI: 10.1080/00461520.2012.722805
- Yeager, D.S., Romero, C.A., Paunesku, D., Hulleman, C.S., Schneider, B.C., Hinojosa, C.P., Lee, H.Y., O'Brien, J.M., Flint, K.L., Roberts, A., Trott, J., Greene, D., Walton, G.M., & Dweck, C.S. (2016). Using Design Thinking to Improve Psychological Interventions: The Case of the Growth Mindset During the Transition to High School. *Journal of educational psychology*, 108 3, 374-391 . DOI:10.1037/edu0000098
- Yeager, D. S., & Walton, G. M. (2011). Social-Psychological Interventions in Education: They're Not Magic. *Review of Educational Research*, 81(2), 267–301.
<https://doi.org/10.3102/0034654311405999>

Appendix

Table A1: Balance test on time spent on MC-Questions

	Time spent on Multiple Choice Questions		
	Control	Treatment	Difference
MC1	10,659	9,915	-0,744
MC2	22,116	23,305	1,189
MC3	31,68	27,83	-3,85***
MC4	17,937	12,921	-5,016***
MC5	12,047	11,555	-0,493
MC6	29,324	30,726	1,402
MC7	24,136	19,812	-4,325
MC8	26,758	24,965	-1,793
MC9	25,257	24,779	-0,477
MC10	15,249	13,559	-1,69
Instruction	296,876	280,684	-16,191

Notes: *p<0,05, **p<0,01, ***p<0,1. Column 1 and 2 show the mean (and standard deviation) from the control and treatment group. Column 3 shows the estimated coefficient (and robust standard error) from different regressions for each covariate against treatment status.

Table A2: Correlation between Post-Treatment Mindset Measures

	Fixed Mindset 1	Fixed Mindset 2	Fixed Mindset IT	Fixed Mindset Effort
Fixed Mindset 2	0,6019**			
Fixed Mindset IT	0,3708**	0,3201**		
Fixed Mindset Effort	0,2373*	0,2088	0,6733**	
Baseline Growth Mindset	0,7465**	0,7230**	0,7918**	0,7105**

Notes: *p<0,05, **p<0,01, ***p<0,1. Post-treatment variable is made by the mean of the four post-mindset measures and standardized with a mean of zero and standard deviation of one.

Table A3: Cross Tabulation

Cross Tabulation on Pre-Intervention Growth Mindset Intelligence and Specialization			
	Fixed Mindset	Growth Mindset	Total
Social Studies	11	30	41
STEM and business Studies	21	25	46
Total	32	55	87

Notes: Cross tabulation of Baseline Growth Mindset Intelligence and Study direction

Table A4: Cross Tabulation

Cross Tabulation on Pre-Intervention Growth Mindset Effort Beliefs and Specialization

	Fixed Mindset	Growth Mindset	Total
Social Studies	26	15	41
STEM and business Studies	34	12	46
Total	60	27	87

Notes: Cross tabulation of Baseline Growth Mindset Effort Beliefs and Study direction

Table A5: Cross Tabulation

Cross Tabulation on Post-Intervention Growth Mindset Effort Beliefs and Specialization

	Fixed Mindset	Growth Mindset	Total
Social Studies	21	20	41
STEM and business Studies	23	23	46
Total	44	43	87

Notes: Cross tabulation of Post-treatment Growth Mindset Effort Beliefs and Study direction

Table A6: Cross Tabulation

Cross Tabulation on Post-Intervention Growth Mindset Intelligence and Specialization

	Fixed Mindset	Growth Mindset	Total
Social Studies	7	34	41
STEM and business Studies	17	29	46
Total	24	63	87

Notes: Cross tabulation of Post-treatment Growth Mindset Intelligence and Study direction

Table A7: Descriptive Statistics on MC-Questions

Descriptive statistics and balance test of multiple-choice questions.			
	Control	Treatment	Difference
MC1	1,024 (0,154)	1,089 (0,288)	0,3 (0,189)
MC2	2,786 (0,470)	2,689 (0,596)	-0,084 (0,096)
MC3	1,238 (0,576)	1,272 (0,544)	0,028 (0,100)
MC4	2,073 (0,346)	2,044 (0,367)	-0,058 (0,153)
MC5	2,905 (0,431)	2,8 (0,588)	-0,099 (0,100)
MC6	1,878 (0,340)	1,977 (0,505)	0,120 (0,115)
MC7	1,976 (0,154)	1,911 (0,358)	-0,211 (0,181)
MC8	2,69 (0,563)	2,622 (0,576)	-0,054 (0,097)
MC9	1,341 (0,575)	1,356 (0,609)	0,010 (0,093)
MC10	2,69 (0,468)	2,4 (0,539)	-0,267** (0,095)

Notes: *p<0,05, **p<0,01, ***p<0,1. Dependent variable listed in each row. Column 1 and 2 show the mean (and standard deviation) from the control and treatment group. Column 3 shows the estimated coefficient (and standard deviation) from different regressions for each covariate against treatment status.

Table A8: Descriptive Statistics. Subsample Social studies

Descriptive Statistics and Balance test. Subsample Social Studies			
	Control	Treatment	Difference
	(1)	(2)	(3)
Fixed Mindset 1	0,055 (1,024)	0,336 (0,646)	0,281 (0,263)
Fixed Mindset 2	0,236 (0,816)	0,172 (0,841)	-0,064 (0,261)
Fixed Mindset IT	0,272 (0,998)	0,114 (1,006)	-0,158 (0,315)
Fixed Mindset Effort	0,211 (0,910)	-0,188 (1,061)	-0,399 (0,313)
Baseline Growth Mindset Intelligence	0,186 (0,870)	0,325 (0,674)	0,140 (0,241)
Baseline Growth Mindset Effort Beliefs	0,272 (0,972)	-0,041 (1,002)	-0,313 (0,311)
Female	0,739 (0,449)	0,611 (0,502)	-0,128 (0,151)
Older than 25	0,304 (0,470)	0,222 (0,428)	-0,082 (0,141)
Mothers Education Level	15,435 (2,019)	14,111 (2,968)	-1,324 (0,815)

Notes: *p<0,05, **p<0,01, ***p<0,1. Dependent variable listed in each row. Column 1 and 2 show the mean (and standard deviation) from the control and treatment group. Column 3 shows the estimated coefficient (and standard deviation) from different regression for each covariate against treatment status.

Invitation to the experiment:

Hei,

Vi ønsker å invitere deg til å delta i et eksperiment ved Handelshøyskolen UIS. Du vil motta 100 kr for å gjennomføre med mulighet til å doble utbetalingen ut i fra resultatet du får. Pengene vil bli utbetalt rett etter eksperimentet.

Eksperimentet krever ingen forkunnskaper. Du skal svare på noen spørsmål, lese to tekster og deretter svare på en multiple-choice oppgave. Eksperimentet varer i omtrent 30 minutter. All informasjon som blir samlet inn i eksperimentet er anonymt.

NB! Alle som deltar må ta med en smarttelefon med tilstrekkelig batteri til 45 minutters bruk.

For å delta, registrerer du deg på linken under og velger det tidspunktet som passer for deg. Vær oppmerksom på at det er begrensede plasser, og kun ledige tidspunkt vil vise på linken.

For spørsmål: kristin_nyboe@hotmail.com

Mandag 8.april kl 10.00
Mandag 8 april kl 12.00
Tirsdag 9 april kl 10.00
Tirsdag 9 april kl 12.00

https://uisnettop.eu.qualtrics.com/jfe/form/SV_eFdOWzYUr6vNmkJ

NB! Påmelding er bindende og det er svært viktig at du møter opp hvis du melder deg på.

Vi gleder oss til å treffe deg!

Med vennlig hilsen,
Christine Kahrs og Kristin Nybø

Instructions on the real-effort task, on how to create a calculator:

Instruksjoner

Det første du må gjøre når du skal programmere er å velge hvilket programmeringsspråk du ønsker å bruke. Noen av de mest vanlige er Java, Java Script og Python. I dette tilfellet har vi brukt Java og programmet Eclipse. Dette kan du laste ned gratis fra internett.

I denne leksjonen skal du lære hvordan du lager en kalkulator, ved å programmere den. Det første du gjør er å lage et nytt Java Prosjekt, og gir dette et navn. Navnet vi har valgt i denne omgang er "Kalkulator". Du må deretter trykke på ditt valgte prosjekt, og velge ny "Windows Builder" og gi dette et navn. Du er nå klar til å starte programmeringen.

Du velger så "Design" helt nede over konsollpanelet ditt og velger formen på kalkulatoren, altså hvordan du ønsker at den skal se ut. Neste steg blir å velge "TekstField" og dra den inn i formen på kalkulatoren din. Du kan også endre størrelse på Tekstboksen din, slik at den får utseende slik du ønsker den. Du kan også velge skrift og skriftstørrelse på teksten inne i boksen. Når du har laget to tekstbokser kan du gå tilbake til programmeringsvinduet ved å trykke på "Source" nede ved konsollpanelet, ved siden av "Design", og kopiere de to tekstboksene du allerede har laget. Koden for hver tekstboks vil da se slik ut, med tall eller bokstav i parentes for "navnet" til hver tekstboks. Dette er for tekstboksen som skal inneholde tallet 0.

```
JButton btn0 = new JButton("0");  
btn0.setFont(new Font("Tahoma", Font.BOLD, 20));  
btn0.setBounds(10, 166, 50, 50);  
frame.getContentPane().add(btn0);
```

Du må også plassere dem riktig på kalkulatoren og det gjør du ved å skrive inn i kodene tallet på hvor de skal plasseres. Her ser du at denne har angitt plass 10, 166. Tallene 50,50 angir størrelsen på tekstboksen, og disse vil være den samme for alle boksene. Det er også en linje for font, og vi har valgt skrift "Tahoma", fonten bold og skriftstørrelse 20.

Neste trinn blir å lage neste rad, og dette kan du enkelt gjøre ved å kopiere koden på de første 4 tekstboksene du laget. Du må da endre på "navnet" i hver tekstboks. Det er også viktig å huske på at plasseringen også skal være annerledes, slik at du også må angi koordinatene på hvor tekstboksen skal plasseres på kalkulatoren. Du må ha med alle tall fra 0 til 9, i tillegg trenger du tekstbokser for å fjerne innholdet, pluss, minus, multiplikasjon, deling, prosent, =, komma og pluss/minus. For punktum må du skrive koden Dot, for å få +/- skrive du inn koden PM, P for pluss og M for minus. For å få en "tilbake-knapp" må du skrive "BackSpace", fjerning av innhold vil få bokstaven C. Du må også ha en tom tekstboks på toppen, hvor du vil få frem resultatene dine når du har programmert kalkulatoren ferdig. Kalkulatoren vil da se slik ut:



Du er nå klar til å programmere den, slik at den får funksjonene til en kalkulator og kan brukes.

Første trinn blir da å høyre-klikke på ett av tallene for eksempel tallet 7, velg "Add Event Handler" og "Action Perform". Du blir da ført tilbake til koden og må skrive inn `String EnterNumber = txtDisplay.getText() + btn7.getText();` På neste linje skriver du inn `txtDisplay.setText(EnterNumber);` Du kan nå trykke på tallet 7 og det vil komme opp i displayet på din kalkulator. Du kan nå kopiere denne koden til alle tallene og knappene på kalkulatoren, slik at du kan bruke alle tastene.

Vi må nå definere noen variabler. Vi skriver da inn `double firstnum;`, `double secondnum;`, `double result;`, `String operations;` og `String answer;`, alle i hver sin linje.

Neste trinn blir å gå tilbake til designet av kalkulatoren og høyreklikke på plusstegnet, velge "Add event handler" og "Action Perform". Vi blir da flyttet tilbake til kodearket, direkte under koden for plusstegnet. Vi må her legge inn kode for at kalkulatoren skal kunne bruke tegnet slik som tiltenkt. I første linje skriver vi da inn `firstnum = Double.parseDouble(txtDisplay.getText());`. Neste linje skal være `txtDisplay.setText("");` og på tredje linje skriver vi inn `operations = "+";`.

Vi kan nå kopiere disse tre linjene og gjøre det samme for minus, deling, multipliser og prosent i kalkulatoren. Det eneste som trengs å endres er at det må være riktig tegn i den siste linjen med kode. Koden for pluss/minus tegnet er noe annerledes. Denne skal være `double ops = Double.parseDouble(String.valueOf(txt.Display.getText()));`, neste linje blir da `ops = ops * (-1);` og tilslutt `txtDisplay.setText(String.valueOf(ops));`.

Vi må nå lagre arbeidet, før vi kan sjekke om den fungerer. Når du har lagret trykker du på den grønne knappen "Run" oppe til venstre. Du får da opp kalkulatoren og kan trykke på knappene og se om den klarer å regne det du ber den om.

Du er nå ferdig å programmere kalkulatoren, og kan bruke den slik du ønsker. Gratulerer!

Multiple-Choice Questions:

1. Hvilket av disse eksemplene er et kjent programmeringsspråk?
 - Python
 - Cava
 - Ritz
2. Hva må du velge for å få en "knapp/boks" i kalkulatoren?
 - Box
 - Button
 - [TekstField](#)
3. For å få tallene frem i displayet må en skrive inn en kode som begynner med?
 - [String EnterNumber =txtDisplay.getText\(\)](#)
 - String EnterNum =txtDisplay.getNum()
 - String EnterNum = tekstDisplay.getNum()
4. Koden for punktum er:
 - P
 - [Dot](#)
 - .
5. Hvilken størrelse har tekstboksene i kalkulatoren?
 - 50:70
 - 60:60
 - [50:50](#)
6. Hvordan skrives koden for å få skrifttype Arial, men bold font og skriftstørrelse 12?
 - Set Font («Arial», Font.BOLD, 12));
 - [Btn0.setFont\(new Font \("Arial", FontBOLD, 12\)\);](#)
 - Bt0.setFont («Arial», Font.BOLD, 12))
7. Hvordan angir du plasseringen på hver "knapp" i kalkulatoren?
 - Drar dem dit jeg ønsker å ha dem med musepilen
 - [Angir tall som koordinater i kodingen av hver "knapp"](#)
 - De legger seg ved siden av hverandre automatisk
8. Hvilken av disse kodene brukte vi for å definere en variabel?
 - double number
 - String number
 - [double firstnum](#)
9. For å programmere kalkulatoren og tallene til å virke etter sin hensikt
 - [Høyreklikket vi på tallet vi ønsket å programmere](#)
 - Trengte ikke å gjøre mer enn å angi hvilket tall som skulle være i hver boks
 - Dobbeltklikket på tallet vi ønsket å programmere
10. Hva må vi gjøre før vi kan sjekke om kalkulatoren virker?
 - Markere hele området med koden
 - Trykke på "Run"
 - [Lagre arbeidet](#)

Illustrative Screenshots of Mindset Measure

Figure A1: Mindset Measure Fixed Mindset 1

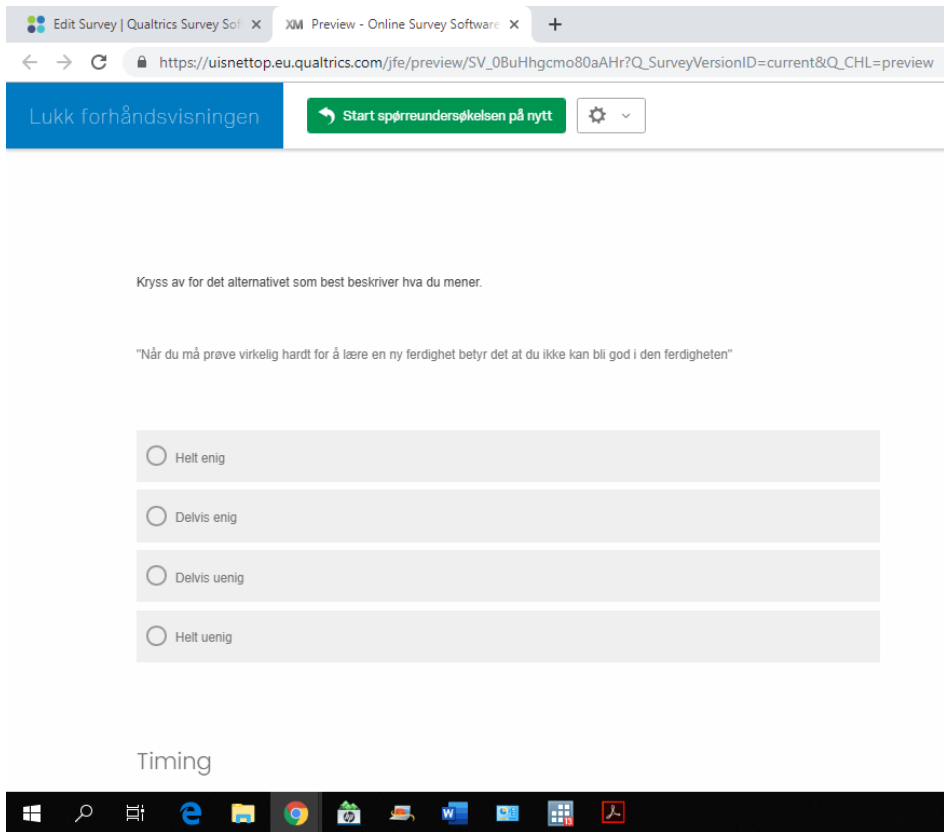


Figure A2: Mindset Measure Fixed Mindset 2

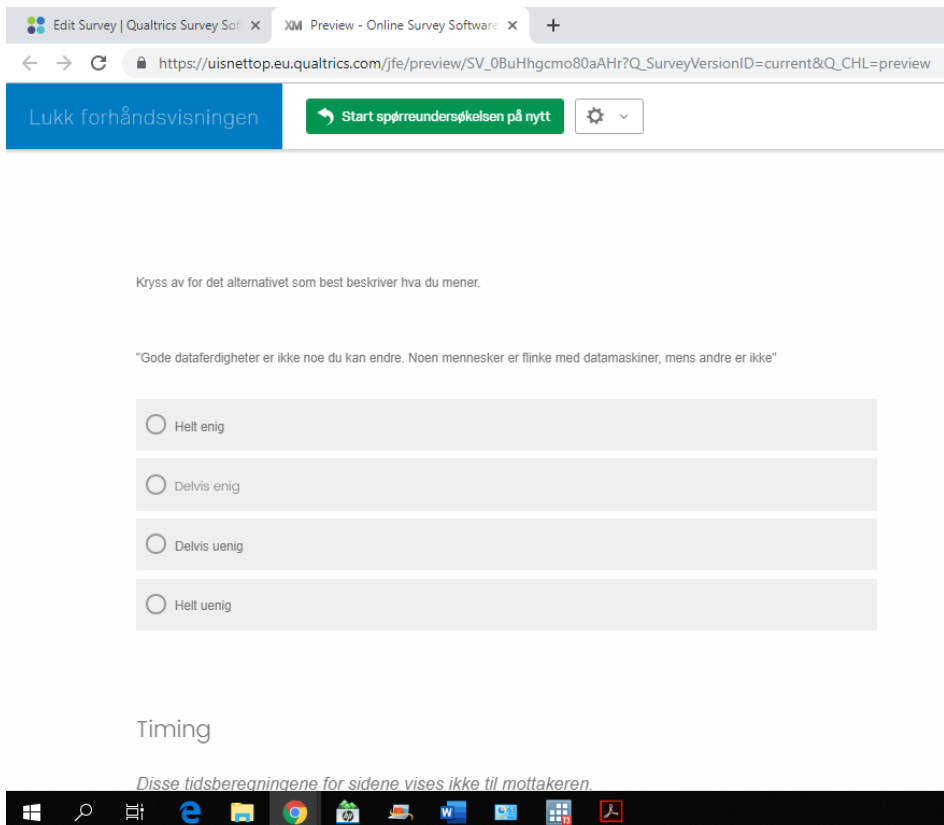


Figure A3: Mindset Measure Fixed Mindset Effort Beliefs & IT

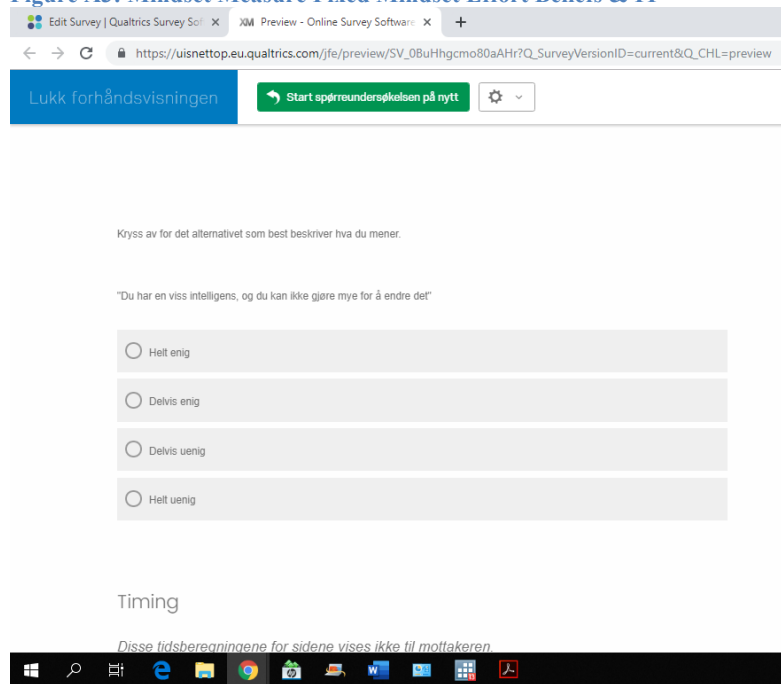
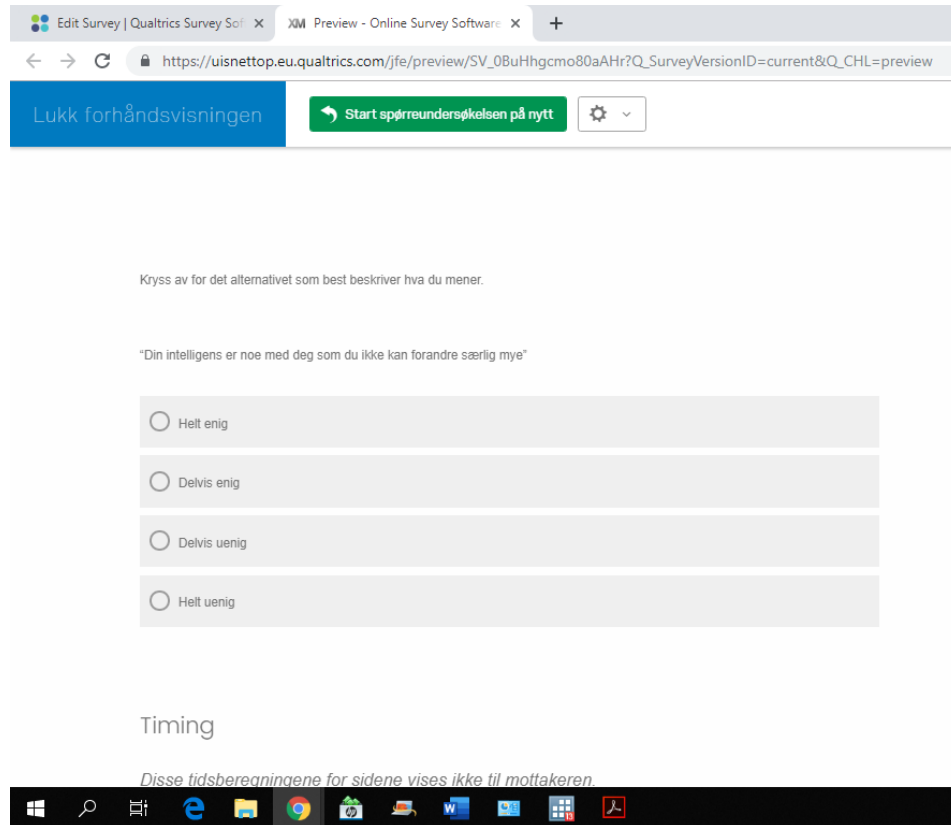


Figure A4: Mindset Measure Fixed Mindset Effort Beliefs

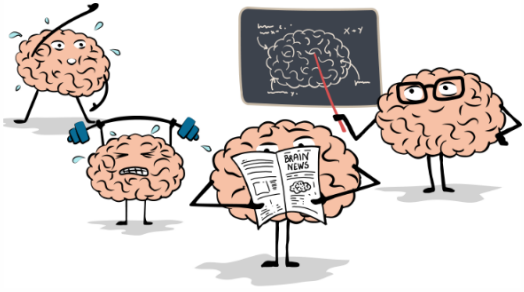


Illustrative Screenshot from the Treatment

Figure A5: Picture from Treatment group

The screenshot shows a web browser window with the URL https://uisnettop.eu.qualtrics.com/jfe/preview/SV_0BuHhgcmo80aAhr?Q_SurveyVersionID=current&Q_CHL=preview. The page content includes:

Nå vil du lære litt om hjernen og hva som skjer i hjernen når vi lærer.



For det første kan hjernen sammenlignes med en muskel - den blir sterkere og smartere når du trener den. Du trener opp hjernen ved å arbeide med oppgaver som gjør at du må tenke hardt.

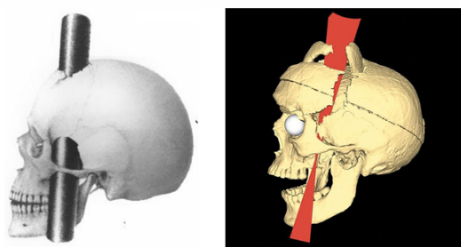
For det andre kan det å øke hjernekapasiteten gjøre det lettere for deg å lære. Slik øker du sjansene for å gjøre det du har lyst til her

The right side of the screenshot shows a mobile phone mockup displaying the same content, including the cartoon illustration and text.

Illustrative Screenshots from the Control

Figure A6: Picture from the Control group

The screenshot shows a web browser window with the URL https://uisnettop.eu.qualtrics.com/jfe/preview/SV_0BuHhgcmo80aAhr?Q_SurveyVersionID=current&Q_CHL=preview. The page content includes:



Hvordan begynte forskerne å lære om hjernen?

Forskerne fikk sin første kunnskap om hjernen ved å undersøke folk som hadde skadet hodet sitt, på forskjellige måter. Et kjent eksempel er jernbanearbeideren Phineas Gage, som for over 150 år siden fikk en metallstang gjennom hodet i en arbeidsulykke. Stangen skjøt opp fra bakken, boret seg gjennom kinnet og hodeskallen hans og videre inn i hjernen.

The right side of the screenshot shows a mobile phone mockup displaying the same content, including the 3D skull models and text.

