Measuring Student Mindsets at Scale in Resource-constrained Settings: A Toolkit with an Application to Brazil during the Pandemic

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Abstract: Mounting evidence that growth mindset – the belief that intelligence is not fixed and can be developed – improves educational outcomes has spurred additional interest in how to measure and promote it in other contexts. Most of this research, however, focuses on high-income countries, where the most common protocols for measuring and intervening on student mindsets rely on connected devices – often unavailable in low- and middle-income countries' schools. This paper develops a toolkit to measure student mindsets in resource-constrained settings, specifically in the context of Brazilian secondary public schools. Concretely, we convert the computer-based survey instruments into text messages (SMS). Collecting mindset survey data from 3,570 students in São Paulo State as schools gradually reopened in early 2021, we validate our methodology by matching key patterns in our data to previous findings in the literature. We also train a machine learning model on our data and show that it can (1) accurately classify students' SMS responses, (2) accurately classify student mindsets even based on text written in other media, and (3) rate the fidelity of different interventions to the published growth mindset curricula.

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1. Introduction

A growth mindset is the belief that intelligence is not fixed and can be developed (Dweck, 2006). Such belief system might influence how adolescents react to challenges at school and their disposition to learn new concepts. Research shows that student mindsets are positively related to math and language grades, especially among the poor; enough to temper the association between income and academic achievement (Claro, Paunesky and Dweck, 2016). Other research demonstrates that a growth mindset may causally improve adolescents' educational outcomes causally (e.g., Rege et al., 2020; Yeager et al., 2019), with effects concentrated in schools where fixed mindsets are most prevalent (Yeager et al., 2022). Recent work explores how student mindsets interact with moderators such as classroom culture, e.g., as expressed through teachers' discourses (Hecht et al., 2023a, 2023b).

Despite the promise of studying mindsets, most evidence comes from high-income countries (in particular, the United States). This is problematic for two reasons. First, survey instruments designed to capture student mindsets might not work as intended in low- and middle-income countries. Mindset interventions typically administer the treatment and collect outcome data through computer- and internet-based surveys. Unfortunately, schools in resource-constrained settings rarely have access to computers and the internet (Brossard et al., 2021). In Brazil, the setting of our study, only 41% of schools had at least one functioning computer, and only 19% had internet speed above 50Mbps (TIC Educação, 2020). Other settings, such as areas under conflict, affected by forced migration or refugee camps may be even more challenging, as face-to-face data collection or access to technology may be difficult or infeasible.

Second, interventions designed to promote a growth mindset might not work as intended in low- and middle-income settings. These interventions may not be attuned to the local context or, even if they are, they may not lead to better educational outcomes. For example, Ganimian (2020) finds that a growth mindset intervention modeled after its US counterpart failed at changing student mindsets in Argentina. The ability to accurately track student mindsets is a key ingredient to rigorously evaluate these interventions in new settings, and to inform policy decisions of which of its aspects should be redesigned, and which should be scaled up.

This paper develops a toolkit to measure student mindsets in low-resource settings. Concretely, we surveyed 92,234 public school students (grades 6-12) over text messages (SMS) in São Paulo State, Brazil, between February and April 2021, as schools gradually reopened to in-person activities after the Covid-19 pandemic. In this context, the lack of computers was not the only constraint. Indeed, face-to-face surveying was impossible due to Covid restrictions on contact throughout that period. Our paper contributes to the growth mindset literature by documenting that the patterns of student mindsets captured through SMS largely match those documented in other settings measured through conventional computer-based instruments.

While text messages have several advantages over computer-based data collection for low- and middle-income countries, they also bring about their own challenges. In particular, responses are not necessarily confined to the level of (dis)agreement with the statements typically used in the literature, regardless of the prompt. As an example, in response to the message 'Do you agree that intelligence is a fixed trait?', one subject replied, "*No, because we are constantly evolving, and the brain adapts to new situations. We have to use our intelligence all the time to monitor these developments.*". While it is straightforward for a human to code that answer as consistent with a growth mindset, it might be impractical to manually rate each response in

a large-scale survey (such as ours, which features thousands of subjects). To deal with that challenge, our toolkit also includes a trained algorithm to classify survey answers automatically. As such, we further contribute to the growth mindset literature by showing that one can automatically classify students' SMS responses with high accuracy. We provide further support for the validity of the classification algorithm by documenting that it can accurately classify student mindsets even based on text written in other media and that it can accurately rate the fidelity of different interventions to the concept of growth mindset.

Our results showcase that it is possible to track student mindsets even in low-resource settings if context-appropriate survey instruments and technologies are used. The paper also paves the way for context-appropriate growth mindset interventions by making all datasets, dictionaries, and codes available for future use by other researchers.

The remainder of the paper is structured as follows. Section 2 outlines the framework for our research program, connecting this study to related research to provide perspective on the many potential applications of this toolkit. Section 3 then provides background on the study's setting and the activities' timeline. Section 4 discusses the insights and lessons learned from our efforts to design context-appropriate instruments, providing detail on the design process which ensured that participants understood the survey questions and that the survey questions captured the psychological constructs of interest. We also show that SMS surveys effectively reached our target population. Section 5 follows with a detailed description of the methods used to validate the toolkit and to train a classification algorithm that can accurately rate SMS responses for future use. Section 6 presents the results. Section 7 concludes the paper.

2. Framework for this research program

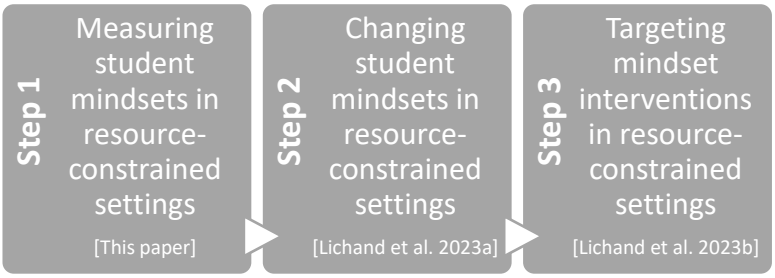
This study is the first of three in a research program on *measuring and supporting student mindsets in resource-constraint settings* (see Figure 1). In this first study, we develop instruments to accurately measure student mindsets in the absence of computer-based surveys. Due to the classification algorithm we make available, this toolkit might be relevant even when phone-based surveys are not feasible.

Once we can measure student mindsets in resource-constrained settings, the second step is to intervene to convert fixed mindsets into growth mindsets – i.e., breeding beliefs that intelligence is malleable, such that a student can always improve relative to him or herself. To ensure interventions are context-appropriate and cost-effective, it is essential to be able to measure their impacts. We take on this task in the second study, the first companion paper (Lichand et al., 2023a) to this one. In that study, we randomly assign 12 different SMS-based growth mindset interventions across Brazilian secondary public-school students – the same population as the one in this study. The paper evaluates the impacts of these interventions on student mindsets (based on the analyses undertaken for this study) and educational outcomes. We illustrate the potential of this connected research program by using our trained classifier to rate the 12 interventions when it comes to their fidelity to the growth mindset concept (see Section 3.4).

Finally, once we have evaluated the extent to which different interventions can promote a growth mindset among students in a resource-constrained setting, the third step in this research program is to target each student with the message most likely both to change their mindset

and to improve their educational outcomes. This is what we take on in a second companion paper (Lichand et al., 2023b) to this study, which uses machine learning models to predict the optimal intervention for each student and then documents the extent to which optimal targeting can make a difference in improving educational outcomes, and whether it can be achieved in practical applications – even with limited data, typical of resource-constrained settings.

Figure 1 – Framework for 'Measuring and supporting student mindsets in resource-constraint settings' research program



Notes: Elaborated by the authors.

3. Background

3.1 Computer-based intervention, survey instruments, and the need for adaptation

The methodology for developing psychological interventions proposed by Yeager et al. (2016) set the stage for future growth mindset studies. Given the effectiveness of this intervention in promoting a growth mindset for 9th-grade students both in the US (Yeager et al., 2016; Yeager et al., 2019) and in Norway (Bettinger et al., 2018), we designed our study both to extend and to test this intervention in Brazil – a middle-income country where secondary education is compulsory, yet less than 60% of students finish high school.

The computer-based protocol has two versions (Yeager et al., 2019): 1) a treatment session, which discusses the malleability of intelligence, explaining the importance of productive struggle and of making mistakes, based on the science of the brain – in particular, highlighting the metaphor that the brain is 'like a muscle' ("the harder one works, the stronger it gets") –; and 2) a placebo session, which merely illustrates how the brain works, focusing on its different anatomical parts and the extent to which different functions are or are not associated with specific brain regions. Typically, researchers randomly assign students to one out of two versions. As part of the session, in both versions, students write letters motivating other students to participate in future sessions. We include illustrations of the introductory screen, treatment version, and prompts asking students to write these letters in Appendix A.

Such letters can be used to classify student mindsets, along with closed-ended questions that elicit the degree to which participants agree with four statements related to the malleability of intelligence:

(1) "You have a certain amount of intelligence, and you really can't do much to change it."
(2) "Your intelligence is something about you that you can't change very much."

(3) "Being a 'math person' or not is something that you really can't change. Some people are good at math and other people aren't."
(4) "When you have to try really hard in a subject at school, it means you can't be good at that subject."

Participants rate each of these statements on a Likert scale (e.g., from strongly/somewhat/weakly disagree to weakly/somewhat/strongly agree). In most applications, subjects are considered to have a growth mindset if they disagree (at least weakly) with all four statements. Numerous studies have used and validated such mindset measures, demonstrating that they strongly predict grades and performance on behavioral tasks.

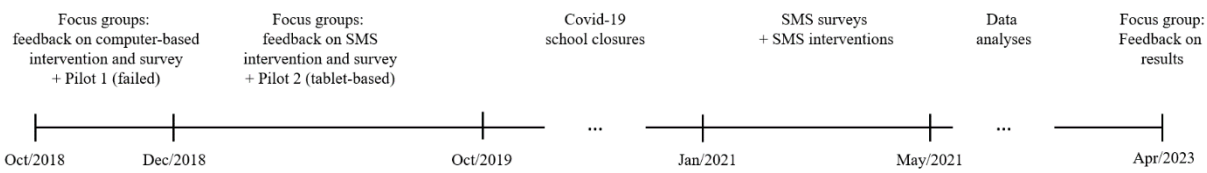
We anticipated two main challenges in applying that instrument in a resource-constrained setting. First, given the severe infrastructure challenges faced by Brazilian public schools, we anticipated that we could not implement a computer-based intervention. Second, given the sociocultural background of our target population, we anticipated that some of these mindset questions would have to be rephrased to effectively capture growth mindset. Both concerns proved to be correct and ultimately led us to not only adapt the intervention and survey instrument to a different format and technology but also write up this paper to document the outcomes of and lessons learned from these adaptations.

3.2 Local partnerships and timeline of field activities

Adapting and testing the intervention relied on partnerships with Rio de Janeiro and São Paulo States' Secretariats of Education. Ranking among the largest student populations in Brazil, these Secretariats navigate complex educational challenges. The São Paulo State Secretariat alone manages a public school system with more than 2 million students, scattered across 1,000 schools.

Figure 2 displays the timeline of our field activities. We started the project in Rio, where we set out to pilot the computer-based intervention and corresponding survey instruments over the last school quarter of 2018. Because of the low availability of functional computers with access to the internet, this first pilot ultimately failed, which ended up being instrumental in the transition to SMS that ensued. In 2019, we were able to pilot both the computer-based intervention (with the help of tablets) and the SMS interventions and survey instruments in Rio.

Figure 2 – Timeline



Notes: Elaborated by the authors.

In 2020, in the face of political transitions in Rio (which made it difficult to keep our study moving forward in the State), we moved the study to São Paulo. We developed the partnership during the period of school closures and rolled out the SMS-based study over the first two school quarters of 2021. We conducted an additional focus group in 2023 to help us interpret our main findings.

4. Designing context-appropriate instruments

4.1 Focus groups prior to piloting the computer-based intervention

We started the adaptation process with feedback from teachers and parents, following the translation protocol developed by Bettinger et al. (2018) for Norway. We elicited feedback through several focus groups over the last school quarter of 2018 and the first two school quarters of 2019. The goal of these focus groups was to leverage the adults in the community and their knowledge of the target population of students to identify potential issues with translating abstract concepts from English to Portuguese.

We opted for a convenience sampling procedure to start the adaptation process quickly. Based on recommendations from the Rio de Janeiro State Secretariat of Education, we contacted the most responsive school representatives to recruit school principals and teachers for this stage of the adaptation process. Two schools agreed to support the initial focus groups and interviews, and eight schools agreed to participate in the pilot.

We recruited eight readily available teachers at one of the partnering schools for the initial focus group. These teachers expressed excitement about the intervention and its potential, voiced concerns about the language and level of abstraction required by the material presented, and suggested modifications to make the language more accessible to the targeted student population. Unfortunately, due to the low engagement of parents with the schools in this context, we were only able to interview two mothers who came to one of the schools to provide feedback on the content developed for the SMS delivery format. While one of the mothers had no difficulty understanding and engaging with the short messages, the other experienced significantly greater difficulty, demanding that each text be explained in multiple ways.

We conducted six focus groups with students, each with 7-8 students. One group examined the placebo content from the computer-based material and helped rewrite the growth mindset instrument so students could better relate. Three groups examined the content of the computer-based intervention, and the remaining two were responsible for examining the intervention content in text message format.

Overall, enumerators leading the student focus groups reported a lack of interest from students, with difficulty in obtaining substantial feedback. In particular, the length of these activities was raised as an issue, as students lost interest quickly. However, some students did engage with the material, with mentions of ‘hope’ that they could learn more and become better at learning, and sparked debates over how to work on it.

Based on this feedback (however thin), we refined the Portuguese version of the computer-based intervention script. In particular, we included additional visual elements (see Appendix A) to make it more appealing to our target age group (12–17-year-olds). An additional adaption provided voice-overs of all text on each screen for a variety of reasons: including students with

special needs, connectivity issues that could get in the way of loading images, and engaging students with low reading proficiency (which are not uncommon in Brazil, even as late as in secondary school). Our hope was to further refine the intervention script following the pilot results.

4.2 Piloting the computer-based intervention

The first pilot study was conducted at the end of the 2018 school year, with a pool of 880 students and parents and 23 teachers across 8 schools. Only 438 students, nine teachers, and 201 parents completed the baseline survey – and even then, with a significant delay. The limitations in equipment and unreliable information about mobile phones made it impossible to collect outcome measures for this pilot.

The implementation challenges faced while running this first pilot revealed two of the major challenges related to the Brazilian public education setting. First, the requirement of opt-in parental consent in this pilot proved to be a significant barrier to recruitment, with an enrollment rate of only 32% of students. Anecdotal evidence offered by school staff suggested that parental engagement with the schools was very low in general, as many of the parents felt unable to contribute or participate in their children's education because they work multiple jobs and had very little formal schooling. Second, schools in this context lacked the basic equipment needed for the computer-based intervention. When available, the only computers with internet access in these schools belonged to the administrative staff office, so only a couple of students could do the computer-based activity at a time.

4.3 Adapting the intervention and survey instruments to SMS

In agreement with the Secretariat of Education, we made three major revisions to the implementation protocol to enable a second pilot study. First, we replaced parental opt-in consent with an assent and opt-out protocol for the parents. Second, we brought in our own tablets to effectively implement the computer-based intervention at schools. Third, we would adapt the intervention and survey instruments to text messages (SMS), such that we could have an alternative media that did not rely on school infrastructure to be rolled out for a subsequent large-scale randomized control trial.

Text messages were appealing because: this capability comes pre-installed in every phone (no need for smartphones); it does not require a data plan (or even airtime, as reverse billing allows participants to reply at no cost); it cannot be uninstalled; and its push notifications cannot be easily turned off. Data plans are expensive in Brazil, where a minimum airtime top-up is of the order of US$ 6. As a result, a recent report indicates that Latin America displays one of the lowest connectivity levels in the world (PWC, 2022). While almost 100% of people have online access at some point during the month, such access is not perennial – averaging only 12 days of connectivity throughout the month (PWC, 2022).

As we discussed the need to transition to SMS, the Secretariat of Education committed to requiring parents to update their mobile phone information upon enrollment every year since parents' phone numbers were either missing or severely outdated, restricting the sample of students who could be assigned to the SMS intervention.

Adapting the growth mindset intervention to the SMS format was a lengthy and complex process led by our implementing partner, Brazilian EdTech Movva (http://movva.tech). The

main challenge was incorporating the key messages from the hour-long computer-based intervention script, filled with rich imagery and supported with voice-over audio, into the SMS format – which is very limited in nature, without capabilities for audio or image, and constrained to 160 characters per message. Movva had extensive experience in running communication with Brazilian public-school students and their families over SMS, and set out to adapt the content of their communication to promote the essential elements of the growth mindset messages present in the computer-based script (see Lichand et al., 2023a, for additional details).

The pilot SMS intervention featured two messages per week over the course of seven weeks, targeting the phone numbers informed as part of the informed consent to participate in the pilot study. The computer-based intervention featured a baseline session, whereby we could measure student mindset before they were exposed to either treatment or placebo content, and an end-line session, conducted approximately a month later.

Initially, we used the same four mindset questions translated into Portuguese for the computer-based intervention, sending them all at the end of the 7 weeks of the pilot intervention.

After extensively piloting the survey questions with our target population to ensure that students could understand the questions and that their answers were consistent with the theoretical constructs, preventing potential mismatches between the instruments and the sociocultural context of the global south, we arrived at the final survey instrument adapted to the SMS format of our main study, as follows:

(1) "Do you agree that if you need to study a subject very hard this means that you are not good at it?"
(2) "Do you agree that intelligence is a fixed trait?"
(3) "Do you agree that doing well or not in math is something that you cannot change?"
(4) "Do you feel unmotivated to study after you receive negative feedback?"

Unlike the computer-based intervention, participants did not have to rate their degree of agreement with statements on a Likert scale. Instead, the statements were rephrased into open questions, and participants could respond to the prompts in any meaningful way. If that potentially creates challenges for manually classifying responses into mindsets, it also potentially creates opportunities to leverage large language models to classify student mindsets using a richer set of inputs automatically.

Participating students received one question weekly over SMS, following the order above. All participants received the same questions each week, and questions rotated every four weeks, for a total of eight weeks.

The study sample comprised 92,234 students (grades 6-12, mainly 12–17-year-olds) eligible for the growth mindset intervention evaluated in Lichand et al. (2023a). All participants received an activation message at the very beginning of our study, explaining that they could opt out of participating in the study by texting a stop word ('cancel,' 'stop,' 'exit') at any point throughout the study.

While high-school students received SMS questions directly on their phone on record, that was not always the case for middle-school students: we targeted them directly whenever their own phone was on record but often had to target their primary caregiver's phone instead. Whenever

the caregiver was asked instead of the student, we changed the framing of the question to make it relational; concretely:

(1) "Do you agree that if *your child* needs to study a subject very hard this means that s/he is not good at it?"
(2) "Do you agree that *your child*'s intelligence is a fixed trait?"
(3) "Do you agree that *your child* doing well or not in math is something that s/he cannot change?"
(4) "Does *your child* feel unmotivated to study after s/he receives negative feedback?"

Even though, in that case, caregivers report mindsets indirectly, we still attribute answers to student mindsets.

All text messages were sent by Movva, in collaboration with the São Paulo State Education Secretariat, to securely access students' and caregivers' phone numbers in compliance with the General Data Protection Regulation.

5. Methods

5.1 Hand-coding SMS responses into mindsets

We started by coding SMS responses manually. This was manageable because of the fairly low response rates (~1%), leading to 5,700 responses (4,534 non-empty and directly related to the survey question; see Section 6.1). Two research assistants independently did the hand-coding, and a principal investigator resolved inconsistencies.

We classified each valid response as either a fixed mindset if its text expresses agreement with the question statement or a growth mindset otherwise. For students with only one valid response over the course of the 8 weeks of data collection, we classified their mindset based on their sole answer. For those with multiple valid responses, we assigned them a fixed (growth) mindset if they (dis)agree with all statements or an undefined mindset if they provide conflicting answers (following Claro et al., 2016).

5.2 Validating growth mindset measurement over SMS against related research

We first validate our results by contrasting key patterns of the data collected over SMS relative to those documented with face-to-face surveys with students in Chile, as reported by Claro et al. (2016).

Concretely, we compare (1) the wealth gradient of growth and fixed mindset, i.e., how the distribution of student mindsets changes as household income increases in each study, and (2) the wealth gradient of math and language grades conditional on student mindsets, i.e., how the distribution of student grades changes as household income increases, separately for those classified as growth or fixed mindset, in each study. We are particularly interested in whether a growth mindset (as captured through our SMS surveys) also tempers with the association between family income and grades, as in Claro et al. (2016).

A challenge of these validation exercises is that we do not have data on household income for our study participants. Instead, we use an imputation procedure as follows. We take advantage of a different study containing both data on household income (classified in brackets for different income ranges, benchmarked to the current minimum wage) and student characteristics for 9th-graders in São Paulo State public schools, collected in 2016 by Lichand et al. (2022). Since both our study and that previous study collected data on student gender, race, math and Portuguese attendance, and math and Portuguese grades, we can predict the income bracket for each student using a Poisson model joint with multiple-imputation methods based on these characteristics, trained in the 2016 dataset. To put it in simple terms, the model simply predicts the most likely income bracket (the value of the discrete distribution) for each student in the 2021 data through a distance minimization procedure, which looks for the most similar students (in terms of their gender, race, and math and Portuguese attendance) in the 2016 data – the only one that features information on actual household income. Importantly, report card grades were not included in the imputation procedure when analyzing whether mindset tempers its relationship with grades. This avoids circularity.

5.3 Validating growth mindset measurement over SMS through focus group discussions

The second way to validate our SMS surveys was through a focus group discussion in April 2023. We recruited three subjects who did not participate in the study but whose profile matched its target population (enrolled in São Paulo State public schools in 2021, at the time of the study).

The focus group facilitator elicited their feedback on the survey instruments used in the study, on using text messages as the media for data collection, and on the main empirical patterns we documented. For the latter, we first asked them to guess the association between gender and mindset, age and mindset, and between mindset and math grades in the data. Then, we showed them the actual results, and asked if they thought they made sense based on their previous discussion.

5.4 Using machine learning to train a classification algorithm

Next, to train a classification algorithm to code students' SMS responses automatically, we use natural language processing (NLP) methods to sort those responses into fixed or growth mindsets. Concretely, we rely on a BERT (Bidirectional Encoder Representations from Transformers) classifier in this study. BERT is a natural language processing model that is based on a pre-trained neural network architecture. We choose BERT because it is pre-trained on large amounts of text data and can learn more nuanced relationships and representations of language compared to other NLP classifiers, such as logistic regression, k-nearest neighbors' algorithms, and SVM (Support Vector Machine). The ability of BERT to capture the contextual meaning and relationships between words in a sentence leads to high accuracy and performance on various NLP tasks, including SMS classification.

We validate the accuracy of the automatic classifier in a variety of ways. First, we train the algorithm in only a portion of the data, holding out a test sample to ensure it can accurately predict classifications out-of-sample. We evaluate the performance of our BERT model by comparing it to our hand-coded classification. Specifically, we assess the overall performance of our BERT model and analyze whether the prediction performance differs according to student groups, sample, and type of text. To run our BERT model, we keep SMS with more

than 3 characters in the sample. We drop all SMS texts that reply ‘yes’ or ‘no’ (in Portuguese). Furthermore, we drop all special characters. In some instances, we do not drop stop words, as we consider them useful in providing context in the architecture of the algorithm (details are always included in the notes to the tables and figures). As the SMS texts are written in Portuguese, we use a locally trained dataset in that language to calculate numerical representations for each token (word). Dictionaries could be easily translated for applications in other settings. We employ a BERT architecture to assign a numerical score between 0 and 1 to each SMS, capturing whether the SMS is associated with a growth mindset (after learning sequences of words and learning the context). Appendix E describes the different steps of our BERT architecture, including fine-tuning, in more detail. We apply our BERT architecture to train models with different texts, including (i) only SMS messages sent by students with more than 3 (or 30) characters; (ii) only sentences of the computer-based intervention script (placebo/treatment scripts); and (iii) a combination of the two.

Second, we validate the algorithm's accuracy is by automatically classifying student responses in a different media – student letters written years before, in the context of the 2019 pilot study of the computer-based intervention, under the treatment and placebo conditions. There, we can check whether the algorithm accurately captures differences in student mindsets across treatment and placebo at the end of both baseline and endline data collections. Concretely, we apply our BERT model trained on the SMS responses sent over 2021 to rate student letters written by participants of the 2019 pilot study. We split letters into sentences and classify each sentence as growth mindset or not based on the trained BERT model. After that, we rate each letter with respect to its fidelity to the concept of growth mindset, computed as the share of its sentences classified as growth mindset. We then use predicted ratings to investigate whether the distribution of student mindsets based on these letters is consistent with the patterns captured through the tablet survey instruments – based on the 6-point Likert scale – in the 2019 pilot study.

Lastly, we use the classification algorithm to rate both the script of the computer-based intervention and the scripts of the SMS interventions evaluated in Lichand et al. (2023a) to showcase its broad applicability to rate the fidelity of mindset interventions to the growth mindset construct. Based on our trained BERT model, we assess 12 different SMS interventions evaluated in the companion study. Specifically, we analyze every text message sent out as part of each intervention, classifying each into a growth mindset or not. We then rate each intervention with respect to its fidelity to the concept of growth mindset, computed as the share of its messages classified as growth mindset.

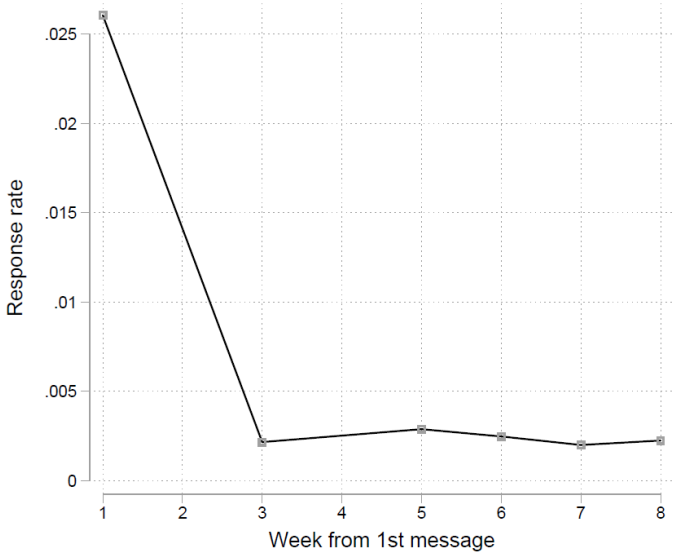
6. Results

6.1 Response rates and respondent characteristics

Considering all growth mindset questions sent out throughout the study, we have 556,645 surveys over the course of the 8 weeks following the activation message. Those prompted 5,700 responses, a roughly 1% response rate. 1,116 out of those were rated as invalid (either empty or not directly related to the question prompt), leaving us with 4,534 valid answers from 3,570 unique subjects – a roughly 4% response rate (relative to the total number of participants). Out of those who provided valid responses, 85% did so only once throughout the study period.

Sustaining participation over time was an even more complex challenge: as Figure 3 shows, participation quickly decays from a response rate above 2.5% in week 1 to less than 0.5% thereafter.

Figure 3 – Response rates over time



Notes: This figure illustrates the response rates for SMS surveys sent during each week of the study. The analysis focuses exclusively on the weeks in which questions were sent out to students (or their caregivers).

A natural concern in the face of low participation rates is the extent to which survey results represent the universe of students. Table 1 shows that other than gender (whose distribution is nearly identical across those who answered at least one question or not), the characteristics of those who responded were systematically different than those who did not. While white participants were slightly more likely to participate in the survey (74% vs. 73%), the main differences related to income levels (based on our imputation procedure), age, and school performance. 34% of those who did not respond lived in households under 1 minimum wage, in contrast to only 29% among those who responded. Middle-school students (or their caregivers) were also over-represented among respondents relative to non-respondents (69% vs. 55%). Last, those who responded were also significantly more likely to display higher attendance and grades in math and Portuguese.

Table 1 – Characteristics of SMS respondents relative to universe

	Did not answered	Answered	Equal means across groups (p-value)
Male	0.51	0.51	0.78
Non-white	0.27	0.26	0.00
< 1 MW	0.34	0.29	0.00
1-4 MW	0.34	0.36	0.00
4-7 MW	0.15	0.17	0.00
8-11 MW	0.06	0.07	0.00
Middle School	0.55	0.68	0.00
Avg. Portuguese report card grade (2020)	6.02	6.21	0.00
Avg. Portuguese attendance (2020)	0.91	0.93	0.00
Avg. Math report card grade (2020)	5.87	6.02	0.00
Avg. Math attendance (2020)	0.91	0.93	0.00
All means equal zero (p-value)			0.00
N	88,664	3,570	
Municipality fixed-effects			yes

Notes: This table displays sample means separately for subjects who responded to the SMS surveys and those who did not, along with two-sided p-values for the null hypothesis that the means are equal across the two groups – absorbing municipality fixed-effects. Gender and race information is reported by students' legal guardians during enrollment. Income brackets are based on the Brazilian 2015 minimum wage, which was R$ 788 then, equivalent to approximately US$ 209. Income data is not routinely collected by the Education Secretariat but was collected by Lichand et al. (2022) for a similar sample in 2016. We impute income brackets for each student using a Poisson model along with multiple-imputation methods, based on student characteristics, trained in the 2016 dataset.

Such differences indicate that it might be important to re-weight our observations with valid survey responses to ensure results are representative of the universe of students. It is worth mentioning that the set of students considered as the universe in Table 1 is that of those with a valid phone number on record by the São Paulo State Secretariat of Education. While that is already a selected sample (in particular, with a lower share of families living in poverty; Lichand et al., 2022), it is the relevant set for those who could have been surveyed through text messages by the Secretariat.

6.2 Student mindsets

Out of the 3,570 subjects with at least one valid answer, we classified 3,332 of them (93%) as either growth or fixed mindset. That is, out of the 15% who answered more than one survey question throughout the study, slightly less than half changed the nature of their answers over time (leading us to classify them as having an 'undefined' mindset, following Claro et al., 2016).

To illustrate the content of the SMS responses, prompted with the question 'Do you agree that your child's intelligence is a fixed trait?', a white male 8th-grader answered, "No, because we are constantly evolving, and the brain adapts to new situations. We have to use intelligence all the time to monitor these developments." We coded this answer as consistent with a growth mindset. When asked, 'Do you agree that doing well or not in math is something that you

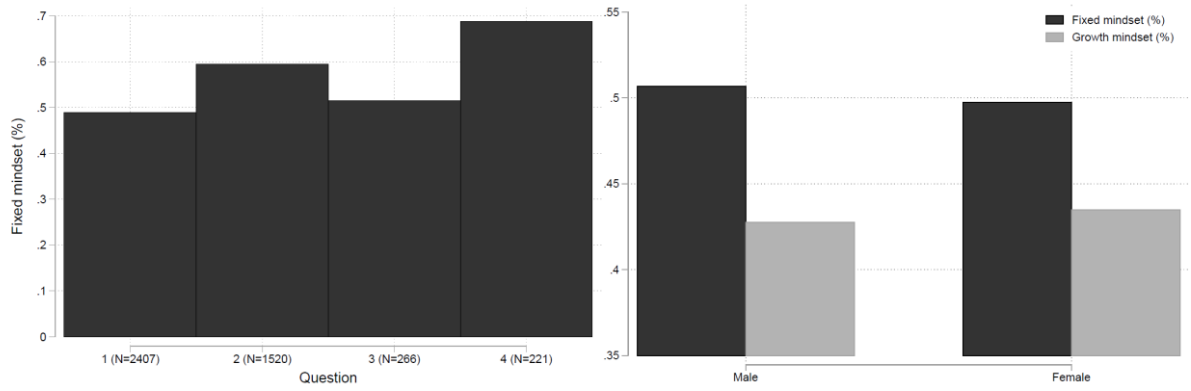
cannot change?', a male 10th-grader of undisclosed race answered, "No, if you have a good teacher, you can be good at it!" We also coded this answer as consistent with a growth mindset. In turn, when prompted with the question, 'Do you agree that your child's intelligence is a fixed trait?', a female 7th-grader of undisclosed race answered, "Yes, I cannot focus on the lessons in this new normal [remote/hybrid instruction] that we are experiencing today. I prefer in-person classes," coded as consistent with a fixed mindset. Similarly, when asked, 'Do you agree that doing well or not in math is something that you cannot change?', a white male 8th-grader answered, "Yes, math is hard. I cannot learn it", also coded as consistent with a fixed mindset.

Figure 4 showcases the distribution of SMS responses by survey question and by student characteristics (gender, race, and grade). About 50% of the responses to 'Do you agree that if you need to study a subject very hard this means that you are not good at it?' and to 'Do you agree that doing well or not in math is something that you cannot change?' were consistent with a fixed mindset. That share was even higher (nearly 60%) when it comes to 'Do you agree that intelligence is a fixed trait?' and reached almost 70% for 'Do you feel unmotivated to study after you receive negative feedback?'.

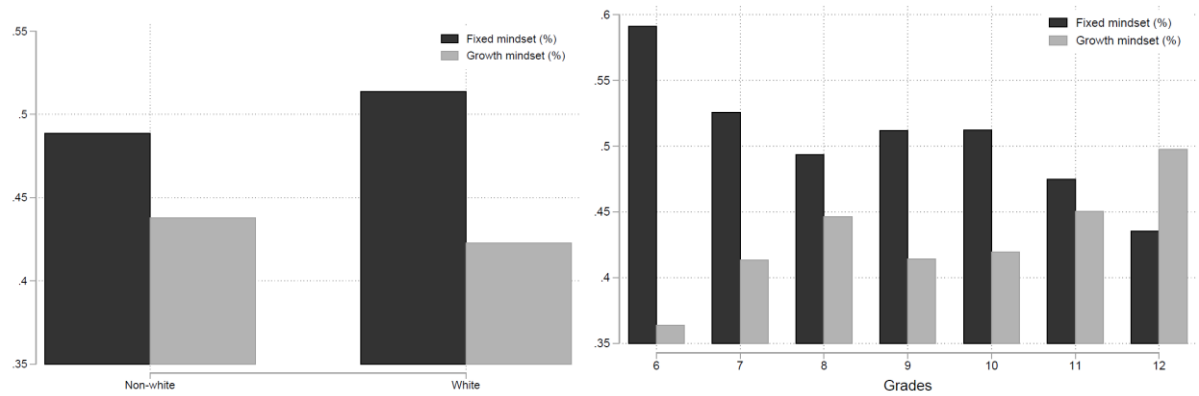
Pooling all survey questions, about 50% of subjects were classified as fixed mindsets and 43% as growth mindsets. That distribution is nearly identical across gender and race, even though white respondents were slightly more likely to be classified as fixed mindsets (and less likely to be classified as growth mindsets).

The most striking differences we documented were by grade: students in earlier grades were significantly more likely to be classified as fixed mindset. Nearly 60% of respondents in grade six were classified as such, in contrast to 44% of those in grade 12. In effect, the prevalence of fixed (growth) mindset nearly monotonically decreases (increases) with the school grade. While that pattern could be reconciled with a positive association between a fixed mindset and the likelihood of dropping out of school, testing that hypothesis would also require collecting data from students no longer at school.

Figure 4 – Student mindset by survey question and by student characteristics



(a) Survey question (b) Gender



(c) Race (d) Grade

Notes: Panel (a) displays the share of SMS responses consistent with a fixed mindset for each of the four survey questions posed to students (or their caregivers). Students are not categorized as neither fixer nor growth mindset if they provide multiple answers over time that are not consistently coded as one or the other. Panel (b) displays the distribution of fixed and growth mindset by gender. Panel (c) displays these distributions by student race. Both gender and race information are reported by students' legal guardians during enrollment. Panel (d) displays mindset distributions by grade.

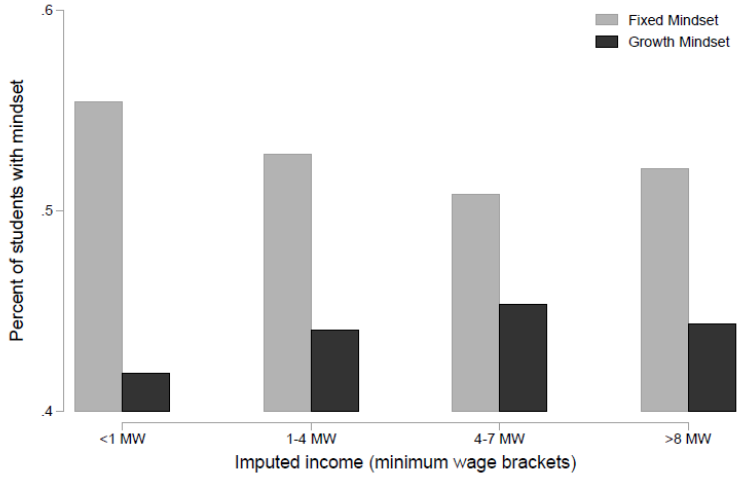
6.3 Comparison with Claro et al. (2016)

To validate our SMS survey methodology, we start by comparing key patterns in our data to those documented in Claro et al. (2016), a study based on face-to-face surveys with Chilean students. The study used the same growth mindset questions as in the computer-based intervention, translated to Spanish—hence, it is directly comparable to our survey instrument.

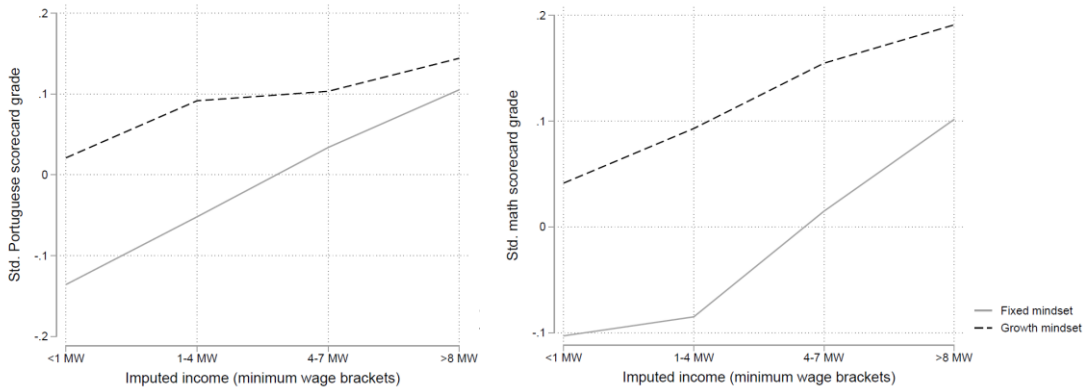
Figure 5 displays the results. Panel (a) plots the prevalence of fixed and growth mindset by family income (based on our imputation procedure). The association between mindset and income in the SMS survey matches the patterns in Claro et a. (2016): higher family income lowers (increases) the likelihood of displaying a fixed (growth) mindset. Such patterns are robust to re-weighting observation by the inverse of the predicted probability of answering the survey based on student characteristics (see Appendix C).

Next, Panel (b) plots the association between report card grades and income separately for students with a fixed or a growth mindset (for Portuguese on the LHS and math on the RHS). Once again in line with the evidence from Chile, results are consistent with the hypothesis that mindset influences the association between poverty and educational outcomes. In effect, moving from a fixed to a growth mindset is equivalent to moving from less than one minimum wage to at least 4-7 minimum wages in terms of standardized grades for both math and Portuguese.

Figure 5 – Validation of SMS mindset measure



(a) Association between student mindsets and family income



(b) Association between report card grades and income, by mindset

Notes: Panel (a) displays the share of students whose SMS responses are consistent with a fixed mindset (grey) and a growth mindset (black) by income bracket. Students are not categorized as neither fixer nor growth mindset if they provide multiple answers over time that are not consistently coded as one or the other. Income brackets are based on the Brazilian 2015 minimum wage, which was R$ 788 at that time, equivalent to approximately US$ 209 back then. Income data is not routinely collected by the Education Secretariat but was collected by Lichand et al. (2022) for a similar sample in 2016. We impute income brackets for each student using a Poisson model, joined with multiple-imputation methods, based on student characteristics trained in the 2016 dataset. Panel (b) displays average Portuguese and math report card grades by income bracket, separately for students whose SMS responses are consistent with a fixed or a growth mindset.

Appendix C compiles additional results, including the average association between student mindsets and report card grades, between the former and standardized test scores, and additional robustness tests for re-weighting observations by the inverse of their probability of answering the survey (predicted with a Probit model based on student characteristics).

6.4 Considerations from focus group discussions

In April 2023, we engaged three former public-school students from the São Paulo State educational system to discuss the previous findings, the survey instruments and our choice of SMS for data collection media. They generally agreed that all four survey questions are tightly

associated with the concept that intelligence is malleable. Interestingly, they all agreed with at least one of the statements. This was more common for the statement linking negative feedback to motivation, consistent with our finding that this prompt was the one most widely associated with fixed mindset responses.

Regarding the choice of text messages, students were initially surprised and skeptical that this was the right survey mode to engage students. One of them said, "I never check my text messages, and I am not even sure I would know how to do it on my new phone." That could help explain the low response rates for our SMS surveys.

While they all mentioned that they use WhatsApp much more frequently, they agreed that many of their peers would not have internet access every day of the month. When they learned that the Secretariat does not even have a valid phone number on record for nearly 50% of the students, they all agreed that it might be preferable to prioritize media with the highest possible reach, even if these media are analog like SMS.

Regarding the survey results, focus group participants expected differences to be much larger in general. For instance, they expected girls and non-white students to have a much higher prevalence of growth mindset relative to boys and white students, respectively in response to teachers' and parents' social expectations that make it harder for the former to thrive in school. As such, they were surprised that this did not appear in the data. They also expected that a growth mindset would be associated with a much larger difference in math and Portuguese grades than in our data. Having said that, they found it valuable that our survey was able to shed light on these issues – even if only to dispel misconceptions about them.

It is also worth noticing that even if a 0.2 grade-point increase in math report card grades (on a scale from 0 to 10) might be perceived as small by focus group participants, the truth is that such difference is actually quite large: as panel (b) in Figure 5 shows, that difference corresponds to more than 0.1 standard deviation., i.e., the typical learning rate over the course of a full school quarter.

All in all, their reactions suggest caution about over-claiming differences in the prevalence of growth mindset by income bracket. While the patterns match those in Claro et al. (2016), the gradient's slope is indeed rather small. In turn, the association between mindset and grades is objectively large (and consistent with the Chilean face-to-face survey data), providing more solid grounds for validating our survey methodology.

6.5 Classifier performance

6.5.1 Descriptive evidence of accuracy

We have students' SMS responses classified into fixed or growth mindsets by human annotators or our BERT model. We start by summarizing the topics students write about in their SMS responses in Figure 6 through word clouds – which report the most indicative words used in responses rated as either fixed or growth mindset, separately for human annotators and BERT predictions. An informal way of assessing the classifier performance is to visually inspect the similarity of the word clouds in the SMS responses most indicative of a given mindset according to the human annotator (LHS) and according to the BERT model (RHS). In the following, as we are less interested in common words to all mindsets, we focus on relative

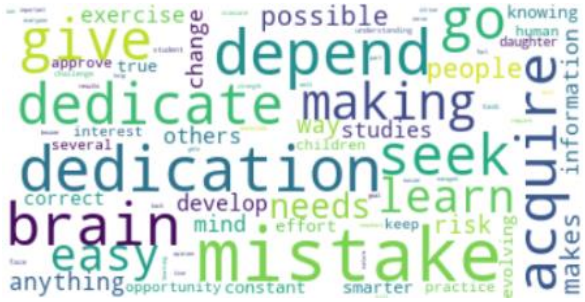
rather than absolute frequencies; the word "learn" is the most used word for both fixed and growth mindsets in the actual and predicted version (not shown).

As shown in Figure 6, words like "dedication," "brain," "change," and, interestingly, "mistake" are related to a growth mindset as classified by human annotators. The corresponding fixed mindset in SMS responses includes "classes," "pandemic," "online," "attention," and even "kill." Although the words based on the predicted models differ somewhat from those based on the human annotations, they are still in line with intuitive concepts of the respective mindsets (such as "intelligence" and "change" for growth mindset, as well as "bad" and "discouraged" for fixed mindset). Furthermore, the alignment of words between the actual and predicted models within a mindset is larger if we use bigrams instead of unigrams (see Appendix C). This makes sense, as the BERT algorithm is based on learning representations through context rather than individual words.

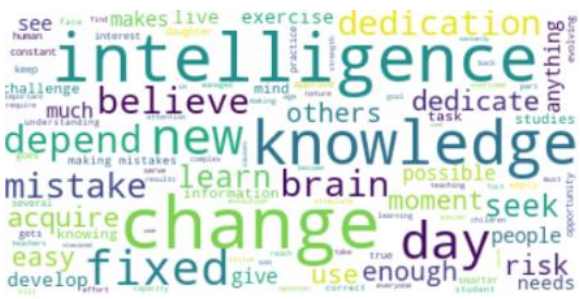
Figure 6: Unigrams for growth mindset (upper graphs) and fixed mindset (lower graphs)

Growth Mindset:

Actual

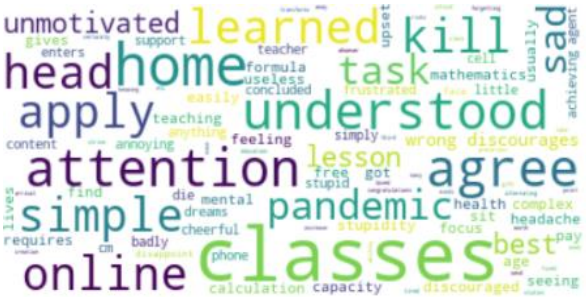


Predicted



Fixed Mindset:

Actual



Predicted

Notes: The figure shows word clouds of unigrams, sorted by mindset (growth vs. fixed) and model ("actual" human annotator vs. "predicted" BERT), based on relative frequencies. The larger the font size, the more important a unigram is for a given mindset in relative terms.

6.5.2 Out-of-sample accuracy in hold-out samples

To formally test the performance of our SMS classifier, we present a confusion matrix in Table 2. A confusion matrix is a visual representation of the performance of a machine learning

model, such as our BERT classifier. It compares the ML-based predictions of whether an SMS is fixed or a growth mindset with our human annotators' corresponding hand-coded labeling. Our confusion matrix consists of four categories: true growth mindsets, true fixed mindsets, false growth mindsets, and false fixed mindsets. True growth (fixed) mindsets refer to the number of cases where the model correctly predicts a growth (fixed). Conversely, false growth (fixed) mindsets represent the cases where the model predicts a growth (fixed) mindset when the actual mindset was fixed (growth).

We use the confusion matrix values to calculate our BERT classifier's performance metrics. First, we compute the accuracy rate, which is defined as the percentage of correct predictions out of all predictions made by the model. The classifier accuracy rate is 0.81, indicating that most SMS responses are correctly classified. However, the accuracy rate may not precisely represent the model's performance, for example, if the dataset is imbalanced (where the number of instances in each class is not equal). To account for this, we also show the F1-score, a metric that combines precision and recall, two important evaluation measures in classification tasks. Precision is the percentage of *accurately predicted* growth mindsets out of all *predicted* (accurately or not) growth mindsets, whereas recall is the percentage of *accurately predicted* growth mindsets out of all *actual* growth mindsets. The F1-score – the harmonic mean of precision and recall – provides a balanced assessment of the model's performance regarding type-1 and type-2 misclassification errors. The F1-score ranges between 0 and 1, where 1 represents perfect precision and recall, and 0 represents very poor performance. We document an F1-score of 0.85, indicating reasonably high prediction accuracy.

Table 2: Confusion matrix

Actual\Predicted	Fixed	Growth
Fixed	51	22
Growth	12	97

Notes: Confusion matrix of actual and predicted growth/fixed mindset SMS. Actual classification was performed by human annotators, and predicted classification was performed by the BERT algorithm. Model training was implemented based on a 70/30 random split for SMS messages larger than 3 characters.

Furthermore, we present a range of additional performance measures to assess the confidence of our model. They built on the insight that our BERT classifier generates a probability distribution of SMS over their possible labels ‘growth mindset’ and ‘fixed mindset,’ indicating how likely BERT thinks each label applies to each response. In this way, BERT can provide a single label prediction and a measure of confidence in that prediction, which can be interpreted as a probability. In the following, we present the overall distribution of the model's predictions and the related performance metric (ROC curve).

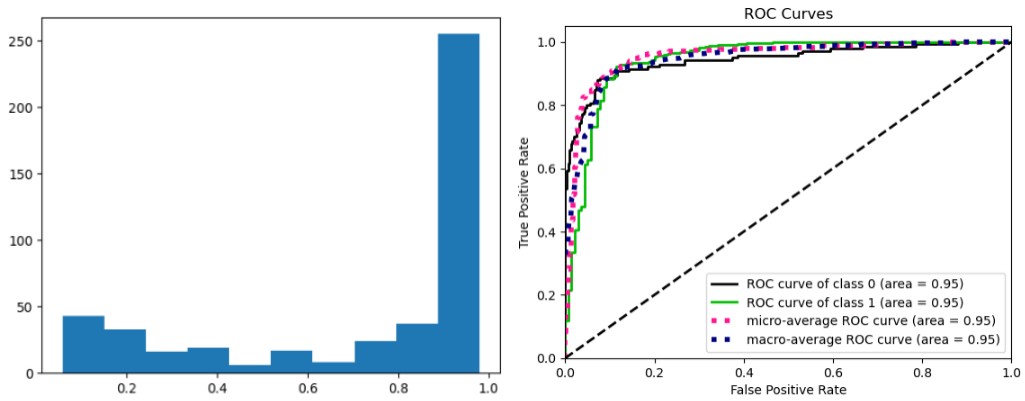
Figure 7 (LHS) showcases the distribution of predicted probabilities of being classified as growth mindset according to BERT. Specifically, the histogram aggregates predicted

probabilities into 10 bins and counts the number of predictions that fall into each bin. The large number of SMS that receive a probability greater than 0.9 indicates that our BERT model classifies SMS at high levels of confidence.

To further assess the performance of our BERT model for different probability thresholds, we calculate an ROC (Receiver Operating Characteristic) curve. The ROC curve is created by plotting the true positive rate (TPR) on the y-axis against the false positive rate (FPR) on the x-axis for different probability thresholds. The area under the ROC curve is a commonly used evaluation metric for BERT. A perfect classifier would have an area of 1, meaning it achieves 100 percent TPR with 0 percent FPR, while a random classifier would have an area of 0.5, meaning it achieves the same TPR and FPR as random guessing. Hence, a high-performing BERT model typically has a steep ROC curve skewed towards the plot's upper left corner.

Figure 7 (RHS) displays the ROC curve of the BERT model, using different thresholds for the probability vector to measure goodness of fit. For different models, we find an area larger than 0.94. This finding, in combination with the other results of this subsection, is consistent with high classification accuracy of our BERT model.

Figure 7: Probability distribution (LHS) and ROC curves (RHS)



Notes: Figure on the LHS depicts histogram of the estimated probability of being a growth-mindset student, according to BERT model. Figure on the RHS depicts ROC (Receiver Operating Characteristic) curve, using different thresholds for the probability vector to measure goodness of fit. The ROC curve for class 0 represents the performance of the model in correctly classifying instances of growth mindset, while the ROC curve for class 1 represents the performance of the model in correctly classifying instances with label fixed mindset. The micro-average ROC curve aggregates the TPR and FPR across growth mindset and fixed mindset and produces a single ROC curve. The macro-average ROC curve computes the TPR and FPR for growth and fixed mindsets separately and then takes the average across the two classes.

Appendix B compiles additional results showing how the classifier's prediction accuracy changes based on different methodological choices for its training and test sets.

6.5.3 Classifier accuracy for rating student letters in different media

Next, we apply our BERT model to predict growth mindset in text written by students in different media, namely, student letters written as part of the tablet-based pilot conducted in 2019. As part of this pilot, students were asked to write letters to future intervention

participants. They were surveyed before and after the computer-based intervention ('baseline' and 'endline' surveys) on various questions, including the computer-based instrument, to elicit their mindset. As mentioned, these questions were the Portuguese version of the English questions in Bettinger et al. (2018), whereby students had to rate the extent to which they agreed with each of the four statements on a Likert scale. We attribute a growth mindset to the letters written by students who weakly or strongly disagree with *all* the statements. All other letters are rated as 'no-growth' mindset, either because the students who wrote them have a fixed mindset (i.e., they weakly or strongly agree with all the questions) or because their mindset is undefined (i.e., they agree with some of the statements but disagree with others; following Claro et al., 2016). Concretely, our goal is to predict growth mindset as revealed by the students in the 2019 pilot study survey by classifying their letters written as part of this pilot using a BERT model trained on the SMS responses sent by the students in the study conducted in 2021. In addition to our main analysis, we employ a modified model that is trained on the combination of SMS by students and the intervention script. We have also trained another BERT model using only the intervention scripts, with modest student letter prediction performance (results available upon request).

To evaluate the prediction performance across models in a concise way, we focus on accuracy and precision. The latter captures the ability to identify growth mindset students correctly, and the former also identifies students who are rated as having either a fixed or an undefined mindset – penalizing models that merely identify all students one way or the other. Table 3 lists the accuracy and precision of each survey, the treatment status, and the BERT model. The reported accuracies range from 39 percent to 72 percent, with a notable pattern by survey and treatment status: while accuracy increases substantially in the treatment group between baseline and endline, it remains constant (or increases to a much smaller extent) in the placebo condition.

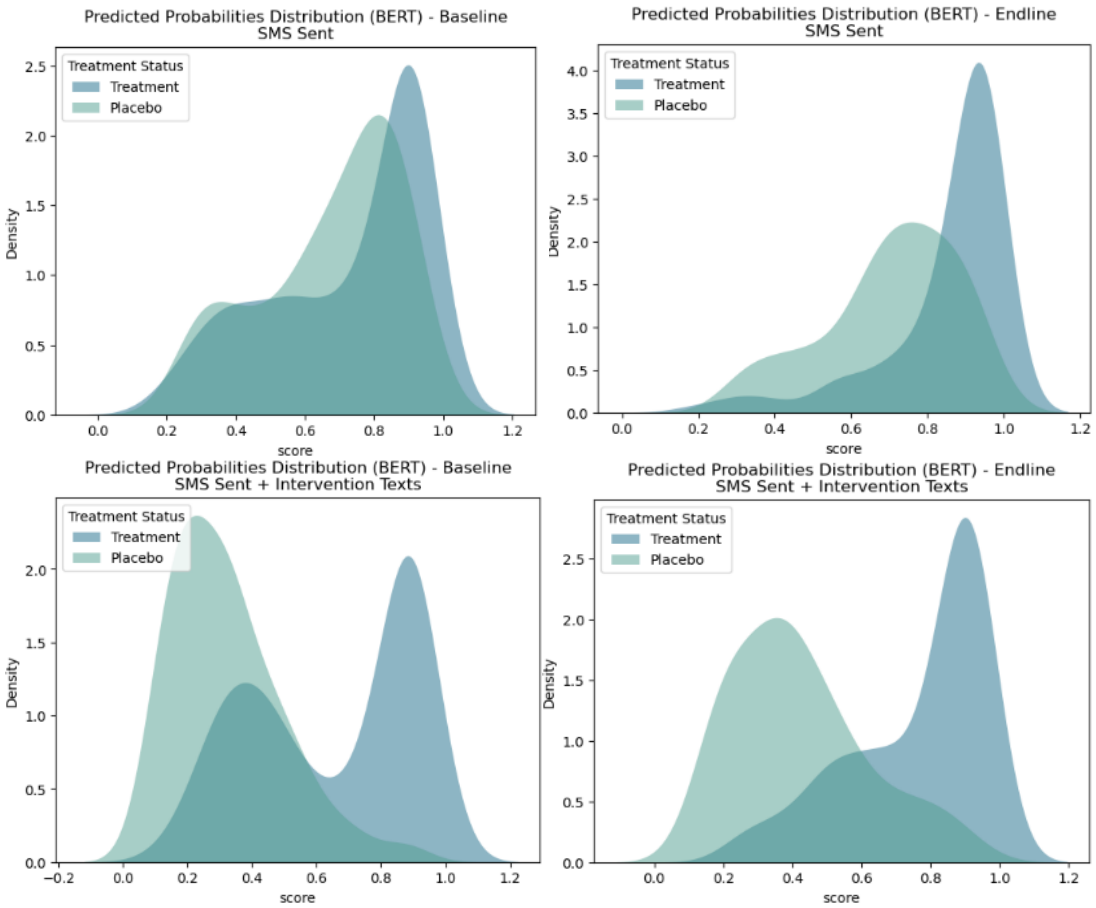
Table 3: Accuracy by survey, treatment status, and BERT model

Survey	Treatment status	Metric	Large-sample models		
			SMS responses	Computer-based intervention script	SMS responses + Computer-based intervention script
Baseline	Treatment	Accuracy	0.628	0.697	0.541
		Precision	0.719	0.712	0.702
	Placebo	Accuracy	0.614	0.468	0.385
		Precision	0.698	0.71	0.769
Endline	Treatment	Accuracy	0.715	0.732	0.672
		Precision	0.754	0.758	0.747
	Placebo	Accuracy	0.605	0.507	0.492
		Precision	0.633	0.591	0.681

Notes: Table presents accuracy and precision, calculated for each survey (baseline and end line) and treatment status (treatment and placebo), and the underlying BERT model, trained on SMS sent by students; and on the combination of SMS sent by students and the set of sentences of placebo (no-growth) / treatment (growth) intervention texts. Accuracy and precision are based on a comparison of BERT predictions, and the student replies when asked about their mindset (growth/no-growth). Predictions based on students' survey responses.

We can further use these BERT models to compute predicted probabilities that student letters correspond to a growth mindset by survey and treatment group. At least for the model trained on the SMS responses only, Figure 8 showcases that predicted probabilities are clearly more divergent at endline. That is consistent with treatment effects on student mindsets based solely on the content of student letters—a striking result.

Figure 8: Predicted probabilities, by survey, treatment status, and BERT model



Notes: Figure shows density of predicted probabilities of replies students wrote in the surveys (baseline/end line) belonging to a growth mindset, calculated for each survey (baseline and end line) and treatment status (treatment and placebo). The first row contains the distributions based on BERT model trained only on SMS sent by students, while the second row contains the distributions of a model also trained on the set of sentences of placebo (no-growth) / treatment (growth) intervention texts.

All in all, we conclude that BERT-based prediction for student letters is also feasible, even if at lower levels of prediction accuracy than the SMS prediction (Section 4.3).

6.5.4 Illustrating an additional application: rating growth mindset interventions

We further illustrate that our BERT toolkit can also be used to rate the fidelity of mindset interventions to the psychological construct. We do so by computing predicted probabilities that content is associated with a growth mindset across 12 different SMS interventions evaluated in a companion study (Lichand et al., 2023a). In that paper, these interventions are grouped into two experiments. Experiment A focuses on the essential elements of the growth

mindset message: (M1) dynamic complementarities in school effort ('your brain is like a muscle,' explored extensively in the computer-based intervention; see Appendix A), (M2) beliefs that return to effort are high, (M3) beliefs that the costs of effort are low, (M4) future orientation, (M5) risk-taking, and (M6) a sense of belonging in the school community. In turn, experiment B considers these very same dimensions but embeds them in practical suggestions of how to get organized for studying as in-person classes gradually resumed over the first two school quarters of 2021.

We use two different BERT models to rate these interventions. The first model is trained on the SMS that students send (using human annotations). The second model is trained not only on the SMS that students send but also on the script of the computer-based intervention. Using both models separately, we predict the probabilities that a given SMS intervention captures a growth mindset and rank the 12 interventions accordingly.

Table 4 lists the 12 interventions, sorted by experiment (A or B) and, within an experiment, by the predicted probabilities to capture a growth mindset based on the first model. Overall, all interventions capture growth mindset rather well, with predicted probabilities ranging from 0.745 to 0.895 across models, experiments, and treatment arms. Although the predicted probabilities are not too different from each other, we can still produce a ranking of interventions. In experiment A, treatment arm M6 captures growth mindset the most, followed by treatment arm M3. This finding holds for the model trained only on SMS sent by students and for the combined model of SMS and intervention scripts. In experiment B, treatment arm M2 captures growth mindset the most, followed by treatment arm M1. Here again, this result holds for both models. Although the full ranking of interventions is not identical for both models, they lead to similar conclusions overall.

Table 4: Predicting Growth Mindset Scores for SMS Interventions

Experiment	Treatment arm	SMS responses	SMS responses + Computer-based intervention script
A	**M6**	0.895 (0.121)	0.84 (0.149)
A	**M3**	0.892 (0.121)	0.838 (0.152)
A	**M1**	0.889 (0.12)	0.825 (0.149)
A	**M5**	0.888 (0.12)	0.812 (0.147)
A	**M2**	0.884 (0.088)	0.85 (0.131)
A	**M4**	0.881 (0.12)	0.805 (0.143)
B	**M2**	0.883 (0.081)	0.85 (0.106)
B	**M1**	0.881 (0.095)	0.836 (0.127)

B	**M4**	0.871 (0.081)	0.745 (0.149)
B	**M5**	0.87 (0.104)	0.793 (0.147)
B	**M6**	0.858 (0.087)	0.811 (0.108)
B	**M3**	0.851 (0.105)	0.767 (0.164)

Notes: Table presents the mean and standard deviation of predicted probabilities that given SMS intervention captures growth mindset by experiment (A and B), treatment arm (M1 – M6), and model (BERT model trained on SMS sent by students, and BERT model trained on SMS sent by students and scripts of computer-based intervention).

A relevant pattern is that, in most cases, the fidelity scores for experiment A are higher than for experiment B. This might help rationalize the findings in Lichand et al. (2023a), which documents that only experiment A significantly increased the prevalence of a growth mindset among targeted students and improved educational outcomes as a result.

7. Discussion

This paper develops a toolkit for measuring student mindsets in low-resource settings – from survey instruments that can be conducted through bare-bones channels such as text messages to a classification algorithm that can automatically classify student responses. Our findings from a large-scale survey based on this toolkit match those of face-to-face surveys collected in Chile, validating our survey methodology. The natural language machine learning model that automatically classifies student responses as fixed or growth mindset trained on our data displays high precision and accuracy relative to hand-coding, showing promise for applications with much larger samples or higher response rates (which are not amenable to manual coding of student responses). In effect, the automatic classifier was successfully applied to rate student mindsets based on letters written in a previous pilot. This application showcases the model's power since it captures the treatment effects of a previous intervention conducted during a pilot study 1.5 years before the data on which the model was trained.

We further illustrated an additional application of this toolkit. The classifier was applied to rate the fidelity of different growth mindset SMS interventions. Results attest to the model's potential, as it attributes higher fidelity precisely to the set of growth mindset interventions that were most effective in changing student mindsets and improving their educational outcomes in a companion study.

This toolkit naturally has several limitations. We study a specific application based on SMS surveys. While we expect it to be widely applicable, since SMS works in any functioning phone (even without connectivity or even airtime), electricity constraints or other issues might prevent the application of phone surveys in specific settings, e.g., among displaced populations. Focus group participants also noticed that, even when SMS is available, it might not be the most effective tool to engage students. In fact, we have experienced substantially low response rates and even more complex challenges in sustaining participation over time, leading to a selected sample relative to the universe of students with phones on record.

Having said that, our results provide evidence that the classifier algorithm trained on the SMS data is applicable even more broadly: it could accurately predict student mindsets when applied to text based on letters written by students using a completely different media. Taken together, the different analyses provide a blueprint of how our SMS toolkit could be applied in practice to SMS responses and beyond. Multimedia applications that combine SMS with other media to broaden the pool of respondents might be particularly promising.

Another important caveat is that while results are encouraging about the possibility of applying our classifiers to other use cases, the sensitivity of the classifier to using the 'voices' of the target population itself (since the model trained on students' SMS responses dominates that merely trained on the computer-based intervention script, even after the latter was adapted to the local context) suggests that, if given the opportunity, researchers should train their own BERT models in their study setting, taking advantage of the step-by-step BERT architecture discussed in Appendix D.

Our BERT model performs well in automatically classifying student mindsets based on their SMS responses. However, the classification accuracy may depend on the medium used to train the model, student subgroups, and a range of coding decisions, highlighting the importance of carefully applying classification technologies. If calibrated successfully, NLP-based technologies like our SMS toolkit can be used to predict text features other than SMS text written by students, as exemplified by the mindset prediction of the student letters and the intervention SMS sent to students.

Our results demonstrate that it is possible to track student mindsets even in low-resource settings, as long as context-appropriate survey instruments and technologies are used. Further research is needed to show the appropriateness of different instruments and technologies for different study populations.

AUTHOR CONTRIBUTION STATEMENT GL, AT, EB and DY contributed to the study conceptualization and design; GL, EA, BA, JG and CD contributed to the study methodology; BA, JG and CD wrote the analyses code; CD was in charge of data curation; GL, BA, JG and EB contributed to writing and editing; and DY supervised the study.

ACKNOWLEDGEMENTS We thank the Rio de Janeiro Municipal Secretariat of Education and the São Paulo State Secretariat of Education for the partnerships that made this study possible.

DATA AVAILABILITY STATEMENT A complete replication package with data, code and models is available at https://osf.io/jk9ue.

ETHICAL APPROVAL STATEMENT Research approved by the Stanford University Institutional Review Board on May 19, 2020 (Protocol # 47710).

PATIENT CONSENT STATEMENT Parental consent for the participation of under-age students in the study was waived by the partner Education Secretariats as the intervention posed minimal risk to participants, while offering significant benefits in expectation. All student data was anonymized before being shared with the researchers, who did not access any data with

personal identifiable information. Students still had to assent before the onset of the intervention, and could opt out at any point by simply texting STOP or CANCEL.

RESEARCH TRANSPARENCY STATEMENT Survey instruments preregistered as part of trials 6436 and 7152 at the AEA Social Science Registry.

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RUNNING HEAD MEASURING STUDENT MINDSETS AT SCALE IN RESOURCE-CONSTRAINED SETTINGS

CONFLICT OF INTEREST STATEMENT GL is a co-founder and chairman at Movva, the implementing partner of the SMS surveys used in this study. EB is a co-director at the Stanford Lemann Center. No other authors have conflicts of interest to disclose.

REFLEXIVITY STATEMENT Based on the framework in Jacobson and Mustafa (2019), we reflected on the positionality of each of the authors relative to the subject matter of this study, and relative to our study population. GL, CD and AT are all Brazilian, grew up in the country, and have been actively engaged with research in education in Brazil since many years now. Nevertheless, they all declare themselves as white and upper middle-class, having studied in private schools, and hence removed from the public-school setting that circumscribes our study participants. JG, in turn, is Colombian. He declares himself as Latino and middle class. His experience in Colombia is similar to that of the Brazilian co-authors – engaged with the issues of public education through his research, although not directly as a student in that system. For all the Latin American authors, being born and raised in the region gives them perspective about the subject matter of this study, as inequalities in educational access, quality and subsequent returns are prominently feature in everyday life in these countries. Last, EA, EB and DY are American, and BA is German. All of them declare themselves as white and (upper) middle class. While they did not directly or indirectly experience the educational journeys of our study population, they have all been long involved in research on international and comparative education, in particular when it comes to documenting and addressing educational inequalities. The lack of first-hand experience of the research team with students' journeys in the Brazilian public education system led us to rely extensively on local partners, particularly the Rio and São Paulo Education Secretariat staff members, and on the several focus groups discussions both prior to running the study, in our consecutive pilots, and after obtaining results, in order to validate our methodology and results with our study population.

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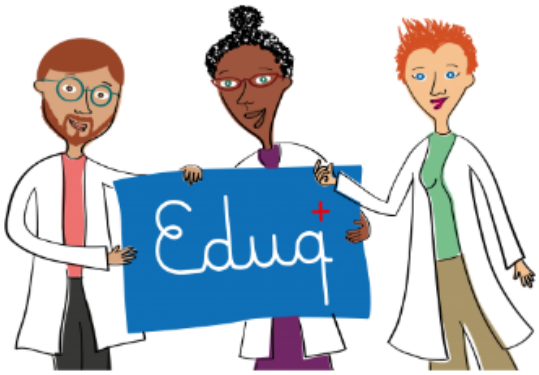
Appendix A – Screenshots from the adapted computer-based intervention

Figures A1, A2 and A3 illustrate the introductory screen, the treatment version, and the prompt for student letters used in our tablet-based pilot. Each figure showcases both the actual application (in Portuguese) and its corresponding English translation.

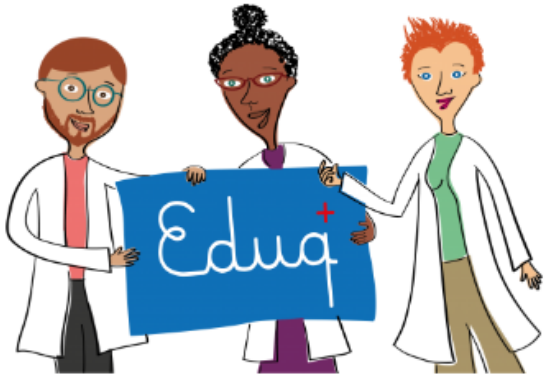
Figure A1. Introductory screen



Qual o nosso objetivo com o Eduq+?
Esse programa foi feito especialmente para você que está no 9º ano do Ensino Fundamental ou no 1º do Ensino Médio na escola." Ele ensina o que acontece com seu cérebro quando você aprende.
Você sabia que a adolescência é um momento perfeito para melhorar a capacidade cerebral e aumentar a inteligência?

Nós não sabemos como é ser adolescente nos dias de hoje, mas você sabe!
Por isso, seus pensamentos e visões de mundo são importantes para melhorarmos esse programa e ajudar jovens como você a reconhecerem seu potencial!

O que você acha?



What is our goal with Eduq+?
This program was made especially for students like you, in 9th grade of elementary school or 1st year of high school." It teaches you what happens to your brain when you learn.
Did you know that adolescence is a perfect time to improve brain power and increase intelligence?
We don't know what it's like to be a teenager these days, but you do!
Therefore, your thoughts and worldviews are important for us to improve this program and help young people like you to recognize their potential!
What do you think?

Figure A2. Treatment version

Trazemos três descobertas científicas bombásticas sobre o cérebro:

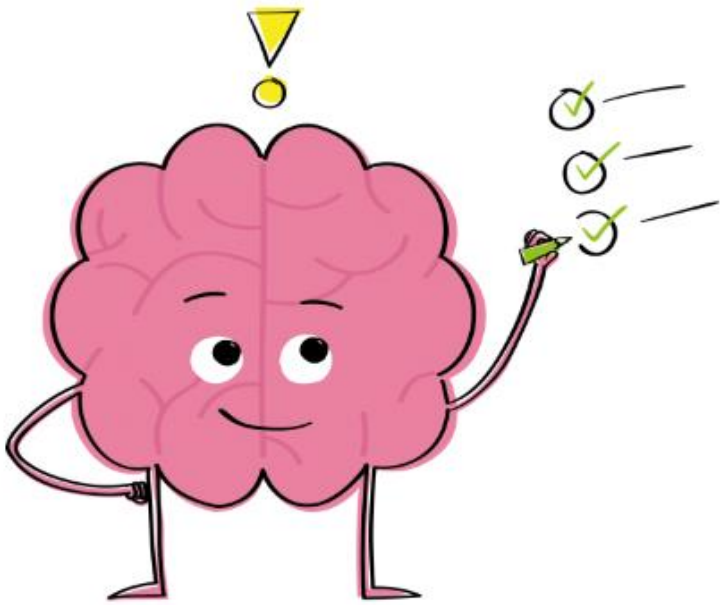
1° Seu cérebro funciona como um músculo que fica mais forte (e mais inteligente) quando você o exercita. Isso acontece quando você faz atividades na escola que exigem que você pense bastante.

We bring three scientific discoveries about the brain:

1° Your brain works like a muscle that gets stronger (and smarter) when you exercise it. This happens when you do activities at school that require you to think hard.

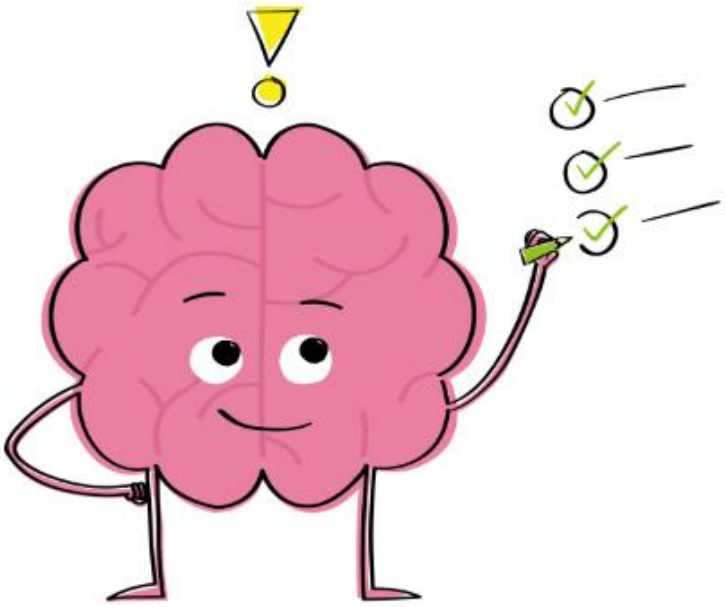
Figure A3. Prompts for student letters

Futuros estudantes precisam de bons exemplos. Você poderia explicar como você conseguiu avançar nos seus desafios usando uma dessas estratégias?



Por favor, escreva uma ou duas frases.

Future students need good examples. Could you explain how you were able to advance through your challenges using one of these strategies?



Please write one or two sentences.

Appendix B – Supplementary discussion of results

B.1 Pilot results

This pilot study was conducted during the first semester of the 2019 school year. We were able to obtain consent from eleven new schools to participate in this pilot, for a total of 636 participating students. Participants were randomly assigned to either the placebo or treatment session of the computer-based intervention, and later randomly assigned to either the SMS intervention or no SMS communication (the control group). Interventions were cross-randomized, such that we could analyze their results separately.

Results revealed a positive and significant effect of both the computer-based and SMS interventions on two out of the four growth mindset questions. Surprisingly, one of the mindset questions ("When you have to try really hard in a subject in school, it means you can't be good at that subject") was associated with a negative impact of both the computer-based and SMS intervention, and we did not find a significant effect associated with either treatment on the remaining growth mindset question.

By aggregating these items into an index, we found suggestive evidence of an overall positive effect for both interventions, with a 0.115 s.d. increase in the probability of displaying a growth mindset for the SMS intervention, and a 0.163 s.d. increase for the computer-based one. Nevertheless, focusing on students that started off with a fixed mindset (measured in the baseline tablet session), we found a divergence between the two formats, as the computer-based was associated with a positive impact on the growth mindset index, while the SMS intervention showcased a negative impact.

Although mixed, these results were encouraging and helped shed light on the potential for improvement of the growth mindset intervention. Thus, we decided to reiterate the adaptation process with new focus groups and a small-scale pilot for the SMS before implementing this intervention at scale.

B.2 Classifier performance by subgroup

Next, we are interested in testing whether the performance of our BERT classifier differs by demographic or socioeconomic groups. Differences in the prediction accuracy across groups could potentially exacerbate student achievement gaps if SMS classification is less precise for underprivileged students, and relevant for student learning at the same time. To investigate this possibility, we merge demographic and socioeconomic characteristics to our main dataset, namely gender, race/ethnicity, and pre-intervention grades in Portuguese and math (grades in the last quarter of 2020). We then calculate the error rate, which is defined as 1 minus the accuracy rate, for the different subgroups.

Table B1 documents no substantial differences in the error rates of subgroups by gender, race/ethnicity, and pre-intervention grades in Portuguese. In contrast, the error rate is substantially lower for the best quarter of students in math (less than 4 percent) compared to the other students. In other words, math is the primary dimension of subgroup differences in classification performance, while the other dimensions are rather unaffected.

Table B1. Error rates, by selected subgroups

By Gender:

Error Rate (Female, 216 students): 0.101

Error Rate (Male, 242 students): 0.099

By Race/Ethnicity:

Error Rate (White, 242 students): 0.103

Error Rate (Mixed, 124 students): 0.096

Error Rate (Black, 11 students): 0.09

By Previous Grades - Portuguese:

Error Rate (Portuguese, Quartile 1): 0.077

Error Rate (Portuguese, Quartile 2): 0.157

Error Rate (Portuguese, Quartile 3): 0.081

Error Rate (Portuguese, Quartile 4): 0.120

By Previous Grades - Math:

Error Rate (Math, Quartile 1): 0.097

Error Rate (Math, Quartile 2): 0.090

Error Rate (Math, Quartile 3): 0.107

Error Rate (Math, Quartile 4): 0.037

Notes: Table presents error rates using BERT predictions, by subgroups of gender, race/ethnicity, and pre-intervention grades (by quartile, for Portuguese and Math, respectively). Sample size differs across subgroup analyses due to varying number of missing observations of student characteristics.

B.3 Classifier performance by sample size

As mentioned in the section on methods and data, we drop SMS with fewer than 4 characters from the main sample. However, this sample still contains a number of SMS with rather limited meaningful content. Therefore, we are interested in learning how the performance of our BERT model changes if we exclude many of the rather meaningless short SMS in the training step. Specifically, we train another BERT model on a sample that keeps all SMS that contain more than 30 characters (the other sample selection criteria, such as the exclusion of special characters, remain unchanged). The training sample is now reduced by approximately 50 percent.

Overall, the performance of this reduced BERT model is largely comparable to the main model. While the accuracy drops from 0.81 to 0.79 in the small model, the F1-score increases from 0.85 to 0.87. Other measures for performance and calibration yield similar conclusions, as reported in Appendix Table D1 and Appendix Figure D2. To evaluate the BERT prediction performance of the small sample, we show a confusion matrix, a probability distribution, and ROC curves. To compare the BERT calibration performance between the large and small sample, we also present a calibration plot that compares the predicted probabilities of a model with the actual probabilities observed in the data. Ideally, a well-calibrated model should have

predicted probabilities that match the actual probabilities, resulting in points of the calibration plot falling close to the diagonal line.

B.4 Classifier performance by type of text

Next, we test whether training the model on another text source (that is also growth mindset related) can yield a similar accuracy for predicting growth mindset in SMS. To this end, we use the script of a computer-based intervention. There are two versions of this script, one containing text about growth mindset that a randomly selected subset of students received, and one containing placebo text that the other students received. The placebo text is unrelated to student mindsets. As such, we refer to it as "no-growth" rather than "fixed mindset".

To train this BERT model, we split each of the two texts into single sentences. First, we use our model trained on the sentences to predict the sentences themselves in a 70:30 test/validation split. This prediction works well, with an accuracy of 80% (additional performance metrics available upon request). Nevertheless, the focus of this analysis lies on testing the predictive power of the script-based algorithm for the students' mindset based on the SMS. As shown in the confusion matrix in Table B2, almost all SMS are predicted to be growth mindset. The accuracy equals 59 percent. This implies that our script-based prediction approach does not work well for distinguishing the two mindsets. Apparently, predicting mindsets using a given medium such as SMS requires corresponding media-specific content.

Table B2. Confusion matrix for BERT trained on computer-based intervention script

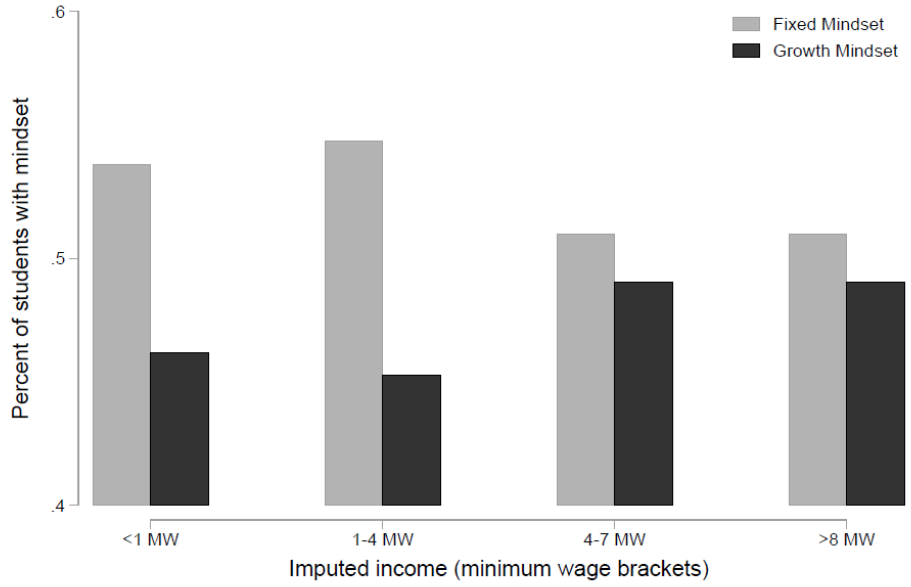
Actual\Predicted	Fixed	Growth
Fixed	2	71
Growth	3	106

Notes: Table presents the confusion matrix of actual and predicted growth/no-growth mindset for all SMS sent by students. Actual classification performed by human annotators, predicted classification performed by BERT algorithm. Model training was implemented based on the whole set of sentences of placebo (no-growth)/treatment (growth) intervention texts.

Appendix C – Additional results and robustness checks

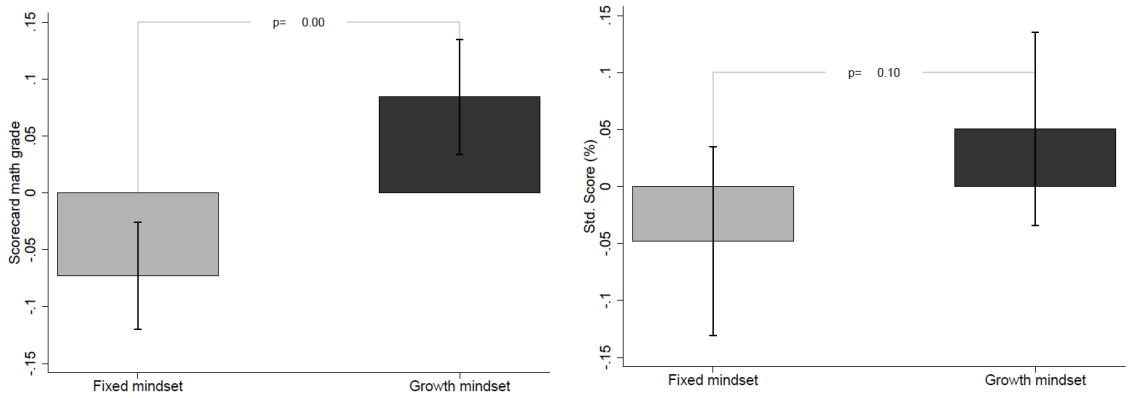
This Appendix compiles additional results and robustness checks for the main results of the paper. Figures C1, C2, C3 and C4 document that the joint distribution of student mindsets and socioeconomic status, that of student mindsets and test scores, and that of socioeconomic status and test scores conditional on student mindsets, are all robust to using inverse probability weights (IPW) to make the sample more similar to the characteristics of the universe.

Figure C1. Robustness to re-weighting observations to match universe of students



Notes: Figure displays the share of students whose SMS responses are consistent with a fixed mindset (grey) and a growth mindset (black) by income bracket, re-weighting observations by the inverse of their predicted probability of providing a valid response to the SMS surveys. Students are not categorized as neither fixer nor growth mindset if they provide multiple answers over time that are not consistently coded as one or the other. Income brackets based on the Brazilian 2015 minimum wage, which was R$ 788 at that time, equivalent to approximately US$ 209 back then. Income data is not routinely collected by the Education Secretariat, but was collected by Lichand et al. (2022) for a similar sample in 2016. We impute income brackets for each student using a Poisson model, joint with multiple-imputation methods, based on student characteristics, trained in the 2016 dataset.

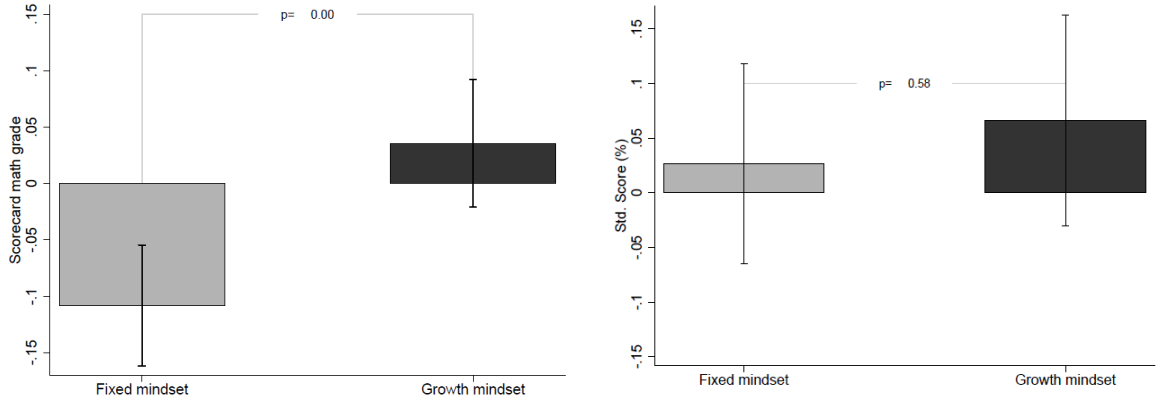
Figure C2. Association between test scores and student mindsets



(a) Math report card grade (b) Math std. test scores

Notes: Panel (a) displays math average report card grades over the 2020 school year, separately for students whose SMS responses are consistent with a fixed or a growth mindset. Panel (b) displays math average standardized test scores over the 2020 school year, separately for students whose SMS responses are consistent with a fixed or a growth mindset. The thin black lines depict 95% confidence intervals. Two-sided p-values for the null hypothesis that averages are equal across fixed and growth mindset students in each case. Report card grades and standardized test scores are normalized relative to the average and standard deviation of the entire sample.

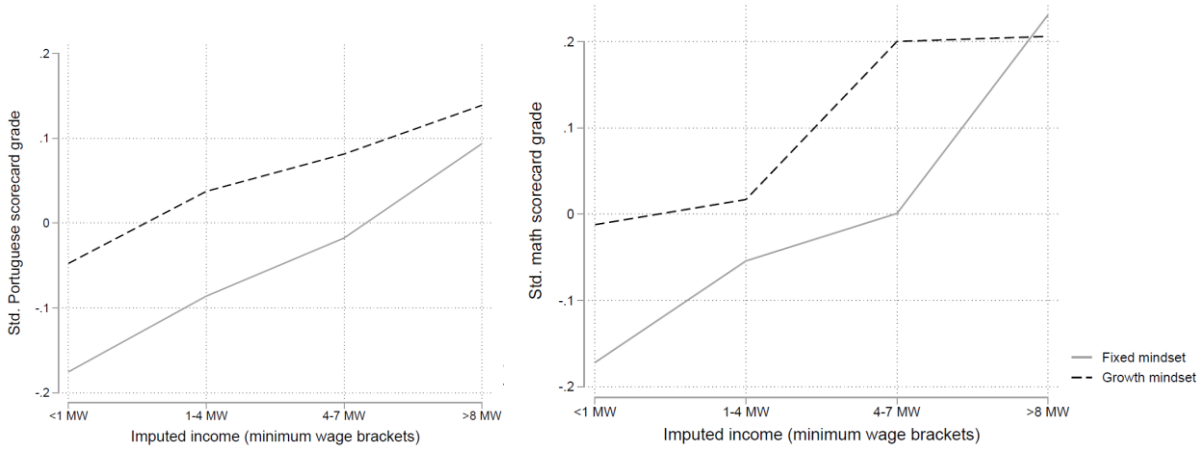
Figure C3. Robustness to re-weighting observations to match universe of students



(b) Report card math grade (b) Math std. test scores

Notes: Panel (a) displays math average report card grades over the 2020 school year, separately for students whose SMS responses are consistent with a fixed or a growth mindset. Panel (b) displays math average standardized test scores over the 2020 school year, separately for students whose SMS responses are consistent with a fixed or a growth mindset. In both panels, we re-weight observations by the inverse of their predicted probability of providing a valid response to the SMS surveys. The thin black lines depict 95% confidence intervals. Two-sided p-values for the null hypothesis that averages are equal across fixed and growth mindset students in each case. Report card grades and standardized test scores are normalized relative to the average and standard deviation of the entire sample.

Figure C4. Robustness to re-weighting observations to match universe of students



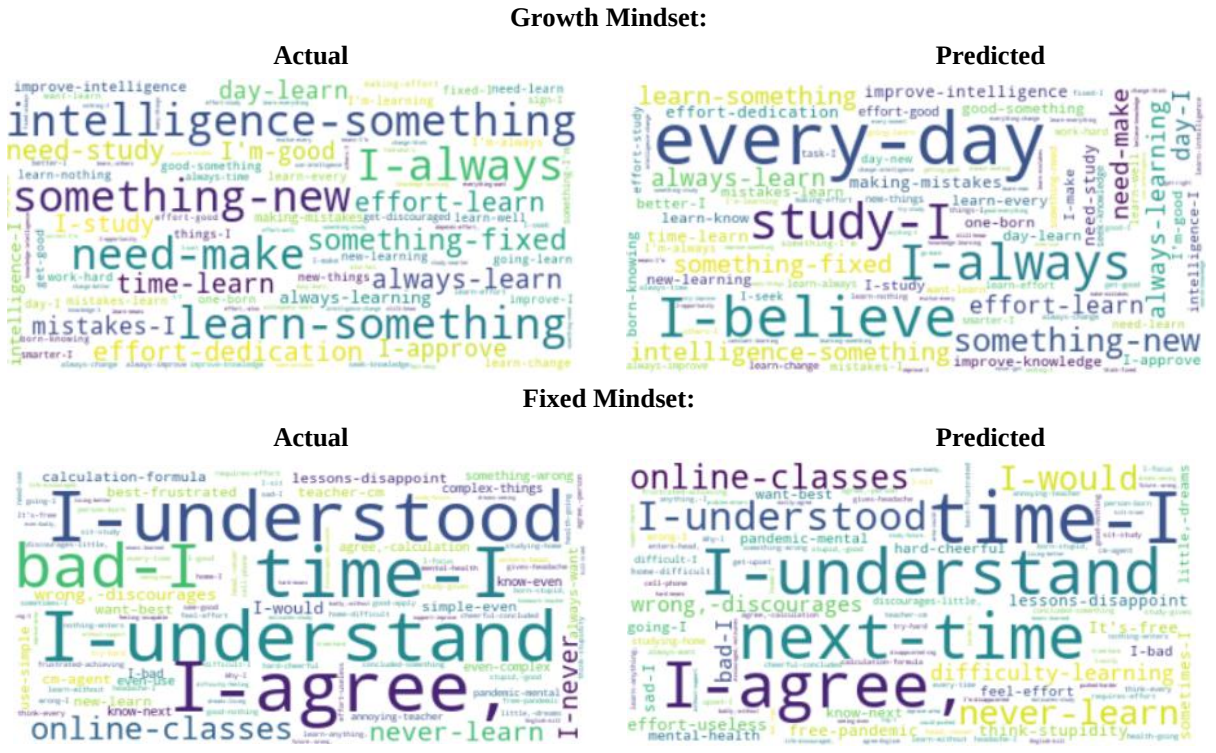
(a) Portuguese report card grade (b) Math report card grade

Notes: Figure displays average Portuguese (Panel a) and math (Panel b) report card grades by income bracket, separately for students whose SMS responses are consistent with a fixed or a growth mindset, re-weighting observations by the inverse of their predicted probability of providing a valid response to the SMS surveys. Income brackets based on the Brazilian 2015 minimum wage, which was R$ 788 at that time, equivalent to approximately US$ 209 back then. Income data is not routinely collected by the Education Secretariat, but was collected by Lichand et al. (2022) for a similar sample in 2016. We impute income brackets for each student using a Poisson model, joint with multiple-imputation methods, based on student characteristics, trained in the 2016 dataset.

Appendix D – Additional results for classifier accuracy

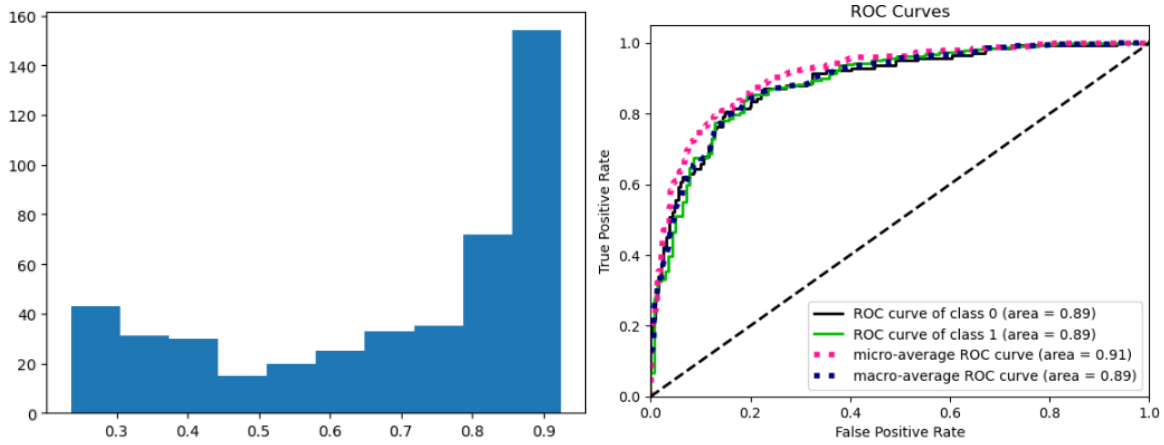
This Appendix compiles additional results for classifier accuracy. Figure D1 showcases word clouds for the bigrams most commonly associated with actual and predicted mindsets. Figure D2 showcases performance metrics for the model trained in the small sample. Figure D3 presents a calibration plot for the large sample (blue) and the small sample (orange), respectively. The points of the large calibration model are a little closer to the diagonal line, with one notable outlier at the mean predicted probability of 0.67.

Figure D1. Bigrams: growth mindset (upper graphs) and fixed mindset (lower graphs)



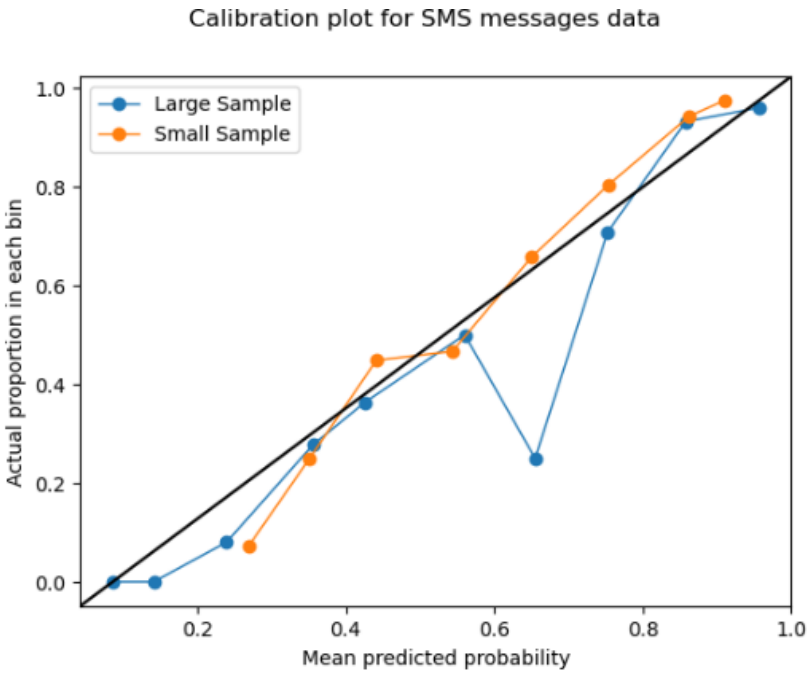
Notes: Figure shows word clouds of bigrams, by mindset (growth vs. fixed) and model ("actual" human annotator vs. "predicted" BERT) based on relative frequencies. The larger the font size, the more important is a bigram for a given mindset in relative terms.

Figure D2. Probability distribution (LHS) and ROC curves (RHS), small sample



Notes: Figure on the LHS depicts histogram of the estimated probability of being a growth-mindset student, according to BERT model. Figure on the RHS depicts ROC (Receiver Operating Characteristic) curve, using different thresholds for the probability vector to measure goodness of fit. The ROC curve for class 0.0 represents the performance of the model in correctly classifying instances of growth mindset, while the ROC curve for class 1.0 represents the performance of the model in correctly classifying instances with label fixed mindset. The micro-average ROC curve aggregates the TPR and FPR across growth mindset and fixed mindset, and produces a single ROC curve. The macro-average ROC curve computes the TPR and FPR for growth mindset and fixed mindset separately and then takes the average across the two classes.

Figure D3. Calibration plot



Notes: Figure depicts calibration plot for two BERT models, trained on a large sample (blue) and small sample (orange).

Table D1. Confusion matrix, small sample

Actual\Predicted	Fixed	Growth
Fixed	16	19
Growth	6	82

Notes: Table presents the confusion matrix of actual and predicted growth/fixed mindset SMS. Actual classification performed by human annotators, predicted classification performed by BERT algorithm. Model training was implemented based on 70/30 random split for SMS messages larger than 30 characters.

Appendix E – BERT architecture

To implement the BERT model, we conduct the following three steps:

1. We start by using the BERTimbau model (https://huggingface.co/neuralmind/bert-base-portuguese-cased) to calculate a numerical vector of 768 dimensions (embeddings) for each token of each message/paragraph. We use its base version due to computational efficiency. The model yields a sequence of vectors for each message. The accuracy of these numerical representations is relatively high as they were calculated using brWaC corpus, which contains 2.68 billions of tokens from 3.53 millions of documents. It is the largest Portuguese corpus to date (Souza et al, 2019).

2. Using each sequence of embeddings, we train a BERT model (Devlin et al, 2018). Intuitively, our BERT model transforms each embedding in each sequence into a weighted average of the embeddings of the sequence (self-attention function), where weights are estimated by a neural network that classifies the sequences of tokens into growth or non-growth/fixed mindset. These weights, based on cosine distances, ultimately allow the algorithm to distinguish mindsets.

3. Before implementing the classification tasks, we fine-tune our model. Following standard practices, we explore which combinations of values of learning rates (2e-5, 3e-5, 5e-5), number of epochs (1,2,3), weight decay (0.001,0), and batch size (16,32) give the highest accuracy. Setting the number of warmup steps to 0, we find that the optimal combination sets the learning rate to 2e-5, the number of epochs to 3, the weight decay to 0, and the batch size to 16 for all models. We perform training/development splits of 70/30 for different combinations of datasets.