Identifying Supportive Contexts for Mindset Interventions: A Two-model Machine Learning Approach

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RESEARCH SNAPSHOT | FALL 2019

Cultivating a growth mindset can help students persist and overcome obstacles they encounter while learning. Interventions designed to foster students' beliefs that their intelligence can grow if they work hard, use effective learning strategies, and ask for help when they need it are one tool to help cultivate growth mindsets; however, research shows that these interventions may be more impactful for some students than others.[1]

In this study, researchers used machine learning methods to automatically examine a wide range of possible factors that might influence the effectiveness of a brief online growth mindset intervention. Understanding for whom, and in what contexts, such interventions work well is crucial as part of broader efforts to understand how educators and other adults can create conditions that promote growth mindsets among students. For example, the messages in the intervention may be presented in a way that resonates with students from some cultural backgrounds but not others. Broadly, results could highlight opportunities to improve curriculum and instruction through the integration of research on growth mindset.

Study Design

In the National Study of Learning Mindsets (NSLM), a random sample of students was assigned to participate in a growth mindset intervention, in the form of an online module completed during two 25-minute sessions. Students read and listened to materials describing scientific evidence about how the brain works and why people can grow their intellectual abilities over time. The program encouraged students to think about why they might want to grow their brain in order to make a difference on something that matters to them, such as their family, community, or a social issue they care about.

The goal of the current study was to examine as many reasons as possible for why the NSLM growth mindset intervention may be more or less effective. Therefore, the researchers analyzed variables including demographic information, psychological factors, grades, and other information collected from students or schools' administrative records.

Key Findings

- Lower incoming grade point average (GPA) and eligibility for free/reduced-price lunch predicted higher future GPA as a result of participating in the growth mindset intervention used in the National Study of Learning Mindsets.
- Prior GPA was the strongest predictor of the effect of the growth mindset intervention on GPA improvement.
- Students' compliance with the intervention activity predicted the intervention's effect on GPA. Specifically, when students tried to move through the intervention too quickly by skipping questions, they benefitted less from the intervention.

Sample

This study leverages data from the National Study of Learning Mindsets (NSLM), the largest-ever randomized controlled trial of a growth mindset program in the U.S. in K-12 settings, in which a brief online growth mindset program was administered to 9th grade students during the 2015-2016 academic year. The NSLM features a nationally representative probability sample of regular U.S. public high schools. Additional information about the NSLM sample of schools and students can be accessed here. The current study used students' demographic information, such as their gender and racial/ethnic background, as well as students' responses to surveys designed to collect information about their attitudes and beliefs. The study focused on the impact of the mindset intervention on students' grade point average (GPA) over time. Thus, only students with GPA information available in the NSLM data set were included in the study, resulting in a sample size of 10,880 students.

MINDSET SCHOLARS NETWORK

The National Study of Learning Mindsets Early Career Fellowship is a project of the Mindset Scholars Network and the University of Texas at Austin Population Research Center. The Mindset Scholars Network is a group of leading social scientists dedicated to improving student outcomes and expanding educational opportunity by advancing our scientific understanding of students' mindsets about learning and school. The University of Texas at Austin Population Research Center aims to provide outstanding infrastructure resources and sustain a dynamic interdisciplinary culture geared toward facilitating the highest level of population-related research among its faculty members and graduate and undergraduate trainees.

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Research Team

- **Early Career Fellow:** Nigel Bosch, University of Illinois at Urbana-Champaign

Areas of expertise: computer science, educational psychology

This snapshot was published at the close of the National Study of Learning Mindsets Early Career Fellowship and captures in-progress work. For more information about this project, please visit this link.

The researchers utilized machine learning methods, which are designed to automatically determine which variables are important and how they relate to outcomes. These methods are particularly useful for cases in which there may be multiple variables that predict the same outcomes, and other complicated relationships between variables and outcomes. Given the large number of possible variables, the researchers also used *regularization*, which is a method intended to encourage machine learning models to discover simpler relationships in data where possible, and *cross-validation*, which is a method intended to correctly evaluate results when there is a strong possibility of discovering relationships between variables that are too specific to a particular subset of data (for example, a similarity among students from one particular school).

This study used two machine learning models. The first model was trained to predict how much GPA would change over time for students who did not receive the NSLM intervention. The researchers then applied this model to students who *did* receive the intervention, thereby estimating the effect of the intervention as the difference between estimated GPA change and actual GPA change. The researchers then trained a second model to predict this difference. Finally, examination of each of these models individually revealed which variables mattered for the magnitude of the impact of the growth mindset intervention on GPA..

Key Findings

Lower incoming grade point average (GPA) and eligibility for free/reduced-price lunch predicted higher future GPA as a result of participating in the growth mindset intervention used in the National Study of Learning Mindsets.

The machine learning methods used in this study yield importance results, which indicate how much influence each variable has on the predictions made by a model. For example, low prior GPA might predict higher future GPA in some cases (where students enter schools with support needed to help them improve), and not in other cases, but on average, low prior GPA was associated with higher GPA improvement.

A key question is the extent to which a growth mindset intervention can improve outcomes for students with lower incoming achievement and from families with greater economic disadvantage. To date, no computer science approaches have been used to address this question, though previous research suggests that growth mindset interventions can be especially powerful for these student groups.[2]

Prior GPA was the strongest predictor of the effect of the growth mindset intervention on GPA improvement.

Prior GPA was the best indicator of how effective the growth mindset intervention would be in terms of GPA improvement. This makes sense because students with a very high GPA are not able to improve their GPA much further; however, students with low or average GPAs may be in a position to benefit more from the intervention. Additional analyses of the machine learning model showed that lower GPA indeed predicted better intervention results (higher GPA improvement) in the model, which is in line with results obtained with traditional statistical methods.[3]

Students' compliance with the intervention activity predicted the intervention's effect on GPA. Specifically, when students tried to move through the intervention too quickly by skipping questions, they benefitted less from the intervention.

The software used to deliver the growth mindset intervention included questions that students were required to complete before they could continue, and recorded cases in which students tried to move on before they were allowed. These records were indicators of whether or not the intervention worked well for students. This finding highlights the importance of clear expectations and an engaging format and delivery when new information is being presented to students.

Insights and Future Directions

It is unsurprising that past academic performance (specifically, GPA) predicts future performance, or that students' experience of socioeconomic disadvantage is associated with GPA. These results are aligned with previous research. It is, however, encouraging that other demographic variables such as race/ethnicity and gender were not strongly related to the effectiveness of the mindset intervention, indicating that groups of students from different backgrounds benefitted equally.

Furthermore, the results showed that monitoring students' participation in the intervention (whether or not they properly completed each step) was key to predicting whether the intervention would be effective or not. Future work might improve the intervention for students who are not fully engaged by making modifications to the instructions or by providing students with feedback about their participation as they progress through the intervention.

The analysis approach used by researchers in this study could also be applied to examine other possible outcomes in the NSLM dataset. Even if a student's GPA does not improve after the intervention, there may be other positive outcomes that could be analyzed. For example, a student might acquire more positive attitudes toward taking on difficult subjects in school, which may result in lower grades but more learning. The same machine learning approaches used in this study can be adapted in future research to predict outcomes like changes in student's self-reported attitudes toward mathematics; in other words, this approach could be used to examine which variables are important predictors for different outcomes, therefore helping to uncover contexts in which the NSLM intervention was most effective for different outcomes.

References

[1] Yeager et al., 2016.
[2] Claro, Paunesku, & Dweck, 2016.
[3] Yeager et al., 2019.

Acknowledgements

Research reported in this summary was supported by the National Study of Learning Mindsets Early Career Fellowship with funding provided by the Bezos Family Foundation. The University of Texas at Austin receives core support from the National Institute of Child Health and Human Development under the award number 5R24 HD042849.

This publication uses data from the National Study of Learning Mindsets (doi:10.3886/ICPSR37353.v1) (PI: D. Yeager; Co-Is: R. Crosnoe, C. Dweck, C. Muller, B. Schneider, & G. Walton), which was made possible through methods and data systems created by the Project for Education Research That Scales (PERTS), data collection carried out by ICF International, meetings hosted by the Mindset Scholars Network at the Center for Advanced Study in the Behavioral Sciences at Stanford University, assistance from C. Hulleman, R. Ferguson, M. Shankar, T. Brock, C. Romero, D. Paunesku, C. Macrander, T. Wilson, E. Konar, M. Weiss, E. Tipton, and A. Duckworth, and funding from the Raikes Foundation, the William T. Grant Foundation, the Spencer Foundation, the Bezos Family Foundation, the Character Lab, the Houston Endowment, the National Institutes of Health under award number R01HD084772-01, the National Science Foundation under grant number 1761179, Angela Duckworth (personal gift), and the President and Dean of Humanities and Social Sciences at Stanford University.

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