How does adopting a Growth Mindset Improve Academic Performance? Probing the Underlying Mechanisms in a Nationally-Representative Sample

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Abstract

Students who are taught that intellectual abilities are not fixed but can be developed—a growth mindset of intelligence—show improvements in their academic outcomes. Specifically, the mindset treatment effects are strongest for low-achieving students and vary across school contexts, as demonstrated by several lab and field-experimental studies including the largest randomized control trial (RCT) evaluation in a nationally-representative sample of 9th graders in the US as shown by the *National Study of Learning Mindsets (NSLM)*. Yet, the mechanisms through which a growth mindset brings about positive academic outcomes remains unclear. Past research posits a role for challenge-seeking/learning-oriented behaviors exhibited by students exposed to a growth mindset intervention. However, research illuminating this pathway from mindset to academic outcomes through student *behaviors* are sparse. For the first time, given the multisite RCT design and the inclusion of a rich set of mediators—especially, a mediator measured using a novel behavioral task that elicits learning-oriented behavior in the NSLM, rather than relying on just self-reported mindset measures, this research tests the complete mediational pathway and highlights a key mechanism through which growth mindset interventions may work.

Keywords: growth mindset, instrumental variable, psychological interventions, randomized control trials, motivation, causal mechanisms

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Introduction

When adolescents are taught that intellectual abilities are not fixed but can be developed—a growth mindset of intelligence—they show improvements in their academic outcomes as evidenced by several lab and field-experimental studies (see Dweck & Yeager, 2019). However, the key mechanisms of change, as evidenced by changes in behaviors, through which such favorable academic outcomes emerge, remain under-explored. For example, when students believe that they can improve their ability, do they work harder? Do they seek out challenging opportunities and other learning experiences? Do they persist when experiencing setbacks or challenging tasks that may be responsible for the positive change in their academic outcomes?

It is crucial to understand behavioral pathways, especially using rigorous, empirical causal inference techniques to further research in this area. Specifically, there has been a call to explore behavioral mediators (Miller, Dannals, & Zlatev, 2017) that may lie in the pathway between the manipulated psychological states and final outcomes of interest (Walton & Wilson, 2018). Indeed, such examination is integral to not just enhance the underlying psychological theory but also to generate policy-relevant insights that can provide practical implications; a task we have undertaken in this present study.

In this study, we integrate two research approaches—theoretically-driven, field-experimental manipulation of mindsets in psychology (Yeager & Walton, 2011) and empirical advances in econometrics and program evaluation in estimating causal mediations using the potential outcomes framework (Neyman, Iwaszkiewicz, & Kolodziejczyk, 1935; Rubin, 1974)—to advance mindset theory regarding the mediating

processes that drive improvements in adolescents' motivation and academic achievement. Specifically, we examined the average causal effect of a key behavioral mediator—students' learning-oriented behavior—induced by the growth mindset intervention implemented in a nationally-representative sample across 65 schools in the US that links manipulated psychological states (the belief that intelligence is malleable) with academic outcomes (grade-point-average [GPA]).

Theoretical and Empirical Background

Decades of lab and field-experimental research have found that students' beliefs or implicit theories are associated with several social-cognitive, motivational, and self-regulatory processes that drive behavior change. In the context of mindset research, across several studies, researchers have illustrated a key role for causal attributions. For example, studies have shown that when students hold a fixed mindset—the belief that intellectual ability cannot change—they were more likely to make fixed trait attributions such as “I’m not smart at math” and adopt negative beliefs about effort (e.g., if “I have to try hard, it means I’m not smart”) (see Leggett, 1986; Miele, Son, & Metcalfe, 2013).

Such attributions and beliefs have been linked to goal-setting processes that have long shown to be key drivers of motivation (Burnette, O’Boyle, VanEpps, Pollack, & Finkel, 2013). For example, in a meta-analytical review of mindset research, Burnette and colleague find that students who did not believe that their intellectual ability is malleable chose performance goals rather than learning goals (2013). Furthermore, studies have also shown that the attributions and effort beliefs that students make may become even more salient or consequential when they experience challenges or

setbacks (Blackwell, Trzesniewski, & Dweck, 2007). Specifically, past research shows that students with a fixed mindset exhibit defensive behaviors especially when experiencing a negative feedback. They chose *not* to take remedial actions that might help them improve or display “symbolic” responses to performance feedback that does not aim to repair their deficit. On the other hand, those students who adopt a growth mindset exhibited learning behaviors, which included remedial actions with the express goal of self-improvement (Nussbaum & Dweck, 2008). In all, past research has suggested (but has not definitively shown using non-self-reported measures) that a growth mindset predicts more learning-oriented behaviors using rigorous methods.

In this vein, we hypothesized that students exposed to the growth mindset intervention would interpret struggles as learning opportunities rather than indications of fixed ability. Subsequently, they are likely to take on more challenges and may be more effortful and persistent. Because the behavioral task was explicitly designed to elicit students’ behavior towards learning, the behavioral measure provides a unique insight into the pathway through which growth mindset interventions might take root to bring about the observed positive academic outcomes downstream. Therefore, there is a strong theoretical basis for our hypothesis on the key behavioral mediator thereby enabling us to illuminate the complete pathway from growth mindset leading to positive academic outcomes.

Econometrically, estimating causal mediating effects even in randomized control trials (RCTs), the “gold standard” of causal inference, is not straightforward because most mediators are not directly manipulated; rather they are measured. However, more recently, empirical methods have been developed to isolate the random variation in

mediators induced by the randomized experimental manipulation (as well as the variation induced across experimental sites in a multisite RCT)¹ to identify the causal effects of various mediators on final outcomes of interest using a multi-site instrumental variables (IV) framework (Duncan, Morris, & Rodrigues, 2011; S. Reardon & Raudenbush, 2013). In effect, IV methods help isolate the “exogenous” variation in the key mediator of interest caused by random assignment to treatment or control groups (see Figure 1). Therefore, the randomization to different conditions, can be used as instruments to isolate the random variation in student behaviors. However, we also have to make several strict identification assumptions under this approach.

Alternatively, mediational analysis in psychology and other social sciences, has traditionally been based on a linear structural equation modeling framework (e.g. Baron & Kenny, 1986; MacKinnon, 2008). Recently, this approach has been extended and placed within the counterfactual framework by including additional identifying assumptions (Imai, Keele, & Tingley, 2010; Imai, Keele, & Yamamoto, 2010). This has enabled causal interpretations of mediation effects under specific assumptions that are somewhat more relaxed than the IV assumptions. Additionally, these methods enable non-parametric estimation and a set of sensitivity analyses within the causal mediational frameworks. In alternative specifications, we include these analyses and test the robustness of our IV assumptions and resulting estimates.

Most recently, the NSLM estimated the average ITT effect as well as heterogeneity in the causal effects of adopting a growth mindset on academic outcomes

¹ A quick note on terminology. I use the term multisite randomized control trial to refer to a design where randomization occurred within each site across multiple sites.

across school contexts (Yeager et al., 2019). However, no previous research has examined whether adoption of a growth mindset relates to *learning-oriented behaviors*—a theoretically-hypothesized mediator in the literature—especially, in a nationally-representative sample, or how the mechanisms may differ across contexts, nor has it exploited such variation to estimate the average causal effect of such learning-oriented behaviors induced by the growth mindset intervention on future academic outcomes.

Data

Data for the current study were drawn from the NSLM—a randomized trial that evaluated a growth mindset intervention—which teaches that intellectual abilities are not fixed but can be developed—in a nationally-representative sample of 9th graders in US public schools (Yeager et al., forthcoming). In the beginning of the 9th grade, students within 65 schools were assigned to either a growth mindset intervention or a control condition. Study participants were followed longitudinally post-intervention for a year with the main academic outcomes measured at the end of their 9th grade and the beginning of 10th grade. Our analysis sample was limited to students who had a valid grade point average calculated for the core academic subjects at the end of the 9th grade.

Measures

Academic outcomes. We use the two pre-registered academic outcomes from the original NSLM: (1) Post-intervention GPA in core 9th grade classes (Math, Science,

English, and Social studies); and (2) Post-intervention GPA in Math and Science 9th grade classes.

Learning-oriented behavior. We operationalize learning-oriented behavior—the key behavioral mediator—in our study using student-reports on a novel behavioral task “make-a-math-worksheet” task (see Yeager et al., 2019 for details). Students completed the task toward the end of the second session, after they completed the intervention (or control content). Students chose from math problems described as challenging (that offered the chance to learn a lot) or as easy (that would not lead to much learning). Students were informed that they could complete the problems at the end of the session if there was time. Past research provides strong support for the validity of this measure (Yeager et al., 2016).

Additional covariates. Additionally, we include student-level covariates—such as prior performance, demographics (student race, gender, parent education), and school fixed effects in alternative model specifications as appropriate.

Methods

Our primary goal was to estimate the average causal effect of students’ learning-oriented behavior on students’ academic outcomes. Conceptually, the basic idea is to isolate a portion of variation in learning-oriented behaviors that is unrelated to unmeasured confound variables and then use only that portion to estimate the linkages between learning-oriented behaviors and achievement (see Figure 1 for the conceptual path model). To accomplish our analytic goals, we follow two primary steps.

First, we isolate the exogenous portion of the learning-oriented behaviors which is induced by the randomized exposure to the growth mindset treatment condition using what is known as the first-stage regression. We specify the regression model as follows:

$$(1) M_{is} = \beta_1 T_{is} + \beta_2 X_{is} + \theta_s + \varepsilon_{is}$$

Where the dependent variable M denotes the mediator, learning-oriented behavior, and T denotes an indicator whether a student was assigned to the growth mindset condition (1= Yes, 0 = No), vector X denotes student-level demographics such as race, gender, baseline academic outcome and others, θ denotes school fixed effects, and ε is a random error term. We estimate all models using ordinary least squares (OLS).

Second, the predicted values, $\widehat{M}_i$, are used in the second stage OLS regression as specified as follows after adjusting for standard errors (to account for using predicted values):

$$(2) Y_i = \gamma_1 \widehat{M}_i + \gamma_2 X_{is} + \phi_s + u_i$$

Where the dependent variable Y denotes the final outcome of interest, GPA for example, and u is a random error term. Now the coefficient γ provides an unbiased causal effect of the estimate of learning-oriented behaviors on academic achievement because it has been purged of all the endogeneity (i.e., the correlation between u and M) by using the randomized treatment status as the instrumental variable.

Because the NSLM was a multisite, person-level randomized study, we can further expand the first and second stage regressions by incorporating site-level variation in the mediating mechanisms as well. We can therefore include site x treatment indicators as multiple instruments. We adapt equations (1) and (2) as follows:

$$(3) M_{is} = \beta_1(T_{is} \times \theta_s) + X_{is} + \varepsilon_{is}$$

$$(4) Y_i = \gamma_1 \widehat{M}_i + \gamma_2 X_{is} + u_i$$

Preliminary Results

Preliminary results show that, on average, the growth mindset intervention increased students' learning-oriented behaviors ($d = 0.22$, $p < 0.001$). As expected, there was considerable heterogeneity in growth mindset induced learning-oriented behaviors across schools. We calculated this heterogeneity in the effect of treatment on the focal mediator following Bloom and colleagues' framework (2017). First, we specify a 2-level multilevel model (students clustered within schools) with school-specific intercepts and a random treatment coefficient that varies across schools. We estimate τ , the standard deviation of treatment effect on the mediator across schools as 0.292. We used restricted maximum likelihood method (REML) for estimating the random effect. To test whether τ is statistically different than zero, we use the Q-statistic proposed by Bloom et al. (2017). The Q-statistic, inspired from meta-analysis used to test cross-study impact variation, can be calculated as the sum of squared standard deviation of a precision-weighted treatment effect estimate on the mediator from site-specific models. Under the null, the Q-statistic follows a chi-square distribution with 64 degrees of freedom (there are 65 sites in the analytical sample). We estimate the Q-statistic to be 89.95 ($p = 0.017$).

Next, using the classic IV framework, we examine the first-stage results of the treatment on the mediator in the full sample using equation (1). As mentioned earlier, we find that a statistically significant treatment effect on the mediator ($\beta = 0.957$, $F = 91.27$, $p < 0.001$). In figure 3, we also visually present the association between site-

specific treatment effect on mediator and site-specific treatment effect on post-intervention GPA across all sites in our analytic sample. A visual inspection shows what Reardon and Raudenbush (2013) call the compliance-effect covariance bias to be small.² We find a very similar pattern when Empirical Bayes estimates of site-specific treatment effects on the mediator and outcomes are plotted. The average difference in treatment effects on post-intervention GPA that differ by one unit in the mediator (assuming no unobserved alternative mediators and that the treatment affects outcomes purely through the observed mediator) can be estimated asymptotically using these methods.

Given the positive first-stage results and strength of the instrument ($F\text{-stat} > 10$), we use 2SLS methods to explore the average causal effect of learning-oriented behaviors on student outcomes approximately one year post-intervention. We find that, on average, the IV estimate is on students' core GPA is 0.063 points ($p = 0.001$) and STEM GPA is 0.07 points ($p < 0.001$), on average, across all schools. For low-achieving (defined based on prior achievement as defined in Yeager et al. (2019)) students, we find that the analogous IV estimate on students' core GPA is 0.124 points ($p = 0.001$) and STEM GPA is 0.126 points ($p = 0.001$), on average, across all schools.

Classic mediation analysis. As mentioned in the “Theoretical and Empirical Background” section, the IV framework we use in this paper contrasts with the nonparametric approach to encouragement designs developed in the methodological literature (Angrist, Imbens, & Rubin, 1996) and applied to the causal mediation analysis

² Under some assumptions, this bias can be numerically estimated in finite sample following (Reardon, Unlu, Zhu, & Bloom, 2014); I hope to include this in the final draft of the paper.

(Imai, Keele, & Tingley, 2010; Imai, Keele, & Yamamoto, 2010; Imai et al., 2013). We will include results from such a causal mediation analysis in the final paper as well.

Discussion

The present research adapted empirical methods stemming from advancements in econometrics and program evaluation to estimate the average causal effect of a key behavioral mediator of growth mindset interventions. Participants exposed to a growth mindset intervention—the belief that intelligence is malleable—exhibited higher learning-oriented behaviors compared with control participants. This effect, however, varies across the 65 schools in which the intervention was implemented. We used this variation to further understand the average causal effect of this behavioral mediator.

In other words, the present research helped illuminate *how* the growth mindset intervention affected academic performance many months later. The increased learning-oriented behavior induced by the intervention, in-turn, mediated the treatment effect on academic outcomes. Previous research did not consistently test for mediation of behavioral processes induced by growth mindset interventions on grades via non-self-reported measures, especially within a rigorous causal inference framework. In high school, adolescents may struggle with increased course loads, might receive negative feedback from teachers on assignments and course materials, and may face several other pressures to perform and get “college ready”. Yet, our study shows that when they are encouraged to view intellectual ability as malleable, they may approach challenging tasks as another effort to learn and improve their skills and abilities rather than just displaying false competence.

Finally, the present study aims to contribute to a new approach for measuring and estimating the causal effect of key mediators to understand the complete causal pathways of interventions better. First, thoughtful measurement of mediators must be operationalized using behavioral tasks that elicit hypothesized behavioral changes rather than just relying on self-report measures. Second, if those mediators can be measured across contexts within a multisite RCT, we can further exploit such context-variation to understand the causal chain in improving adolescents' outcomes.

Tables and Figures

Figure 1. Path Model

Figure 2. First-stage Results. Effects of Treatment on Learning-Oriented Behaviors

Figure 3. Association Between Site-Specific Effect of Treatment on Mediator and Site-Specific Effect of Treatment on Academic Outcomes

Table 1. Descriptive Statistics of Key Variables (Unweighted)

Key Characteristics	Analytic Sample		
	<i>Mean</i>	<i>SD</i>	<i>n</i>
Learning-Oriented Behavior	-0.66	3.78	11,628
Academic Outcomes			
Post-Intervention Core GPA	2.60	1.07	12,488
Post-Intervention Math/Science GPA	2.51	1.14	12,086
Student Characteristics			
Female	0.49	0.50	13,421
Maternal College Education	0.29	0.45	13,421
Asian	0.04	0.19	13,421
Black	0.11	0.32	13,421
Hispanic	0.24	0.43	13,421
White	0.43	0.50	13,421

Table 2. Preliminary Results (Full Sample)

	Average Post-Intervention GPA		Average Post-Intervention Math and Science GPA	
	<i>OLS</i>	<i>2SLS</i>	<i>OLS</i>	<i>2SLS</i>
Treatment	0.052*** (0.016)		0.066*** (0.018)	
Learning-Oriented Behavior		0.063*** (0.018)		0.070*** (0.02)
Site Fixed Effects	X	X	X	X
Treatment as Instrument		X		X
Post-stratification Weights	X	X	X	X
Other Student-level Covariates	X	X	X	X
Number of Observations	12,488	10,955	12,086	10,678

Notes: Asterisks denote significance at the 0.1% (***), 1% (**), and 5% (*) levels. Robust standard errors in parentheses and clustered at the school-level.

Table 3. Preliminary Results (At-risk Students)

	Average Post-Intervention GPA		Average Post-Intervention Math and Science GPA	
	<i>OLS</i>	<i>2SLS</i>	<i>OLS</i>	<i>2SLS</i>
Treatment	0.100*** (0.024)		0.103*** (0.027)	
Learning-Oriented Behavior		0.123*** (0.037)		0.127*** (0.038)
Site Fixed Effects	X	X	X	X
Treatment as Instrument		X		X
Post-stratification Weights	X	X	X	X
Other Student-level Covariates	X	X	X	X
Number of Observations	6,325	5,434	6,146	5,313

Notes: Asterisks denote significance at the 0.1% (***), 1% (**), and 5% (*) levels. Robust standard errors in parentheses and clustered at the school-level.

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