The Causal Impact of a Growth Mindset Intervention on Student Achievement

AUTHOR: SHRUTHI NANDITHA GANESH (sg2057)

INTRODUCTION / MOTIVATION

Academic achievement is shaped not only by intelligence or socioeconomic factors, but also by students' beliefs about their ability to grow and learn. A *growth mindset*—the belief that intelligence can be developed—has been shown to improve academic performance, especially among underperforming students. While randomized controlled trials have demonstrated its effectiveness, there is limited evidence on how mindset interventions perform in **real-world, non-randomized educational settings**. This study investigates whether a low-cost, scalable growth mindset intervention causally improves student achievement using **observational data** from U.S. high schools and applies robust causal inference techniques.

DATA EXPLORATION

The dataset includes over 10,000 high school students across the U.S., with variables covering academic performance, self-reported expectations, demographics, and school characteristics.
Preliminary exploration revealed **differences in outcome distributions** across treatment groups and **imbalances in baseline characteristics** like gender, mindset scores, and school size.

DATA EXPLORATION

We used multiple causal inference methods to estimate the Average Treatment Effect (ATE) of the mindset intervention:

- **Descriptive comparisons** of outcome means across groups
- **Regression adjustment** controlling for covariates
- **Propensity score modeling** via logistic regression
- **IPW and AIPW** to adjust for selection bias and improve robustness

Key Assumptions:

- **No unmeasured confounders** (strong ignorability)
- **Positivity**: all students had a non-zero chance of receiving treatment
- **Correct model specification** for outcome and propensity models

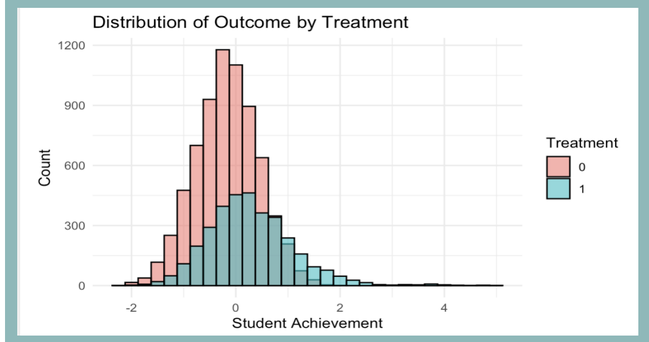
METHODOLOGY

Preprocessing:

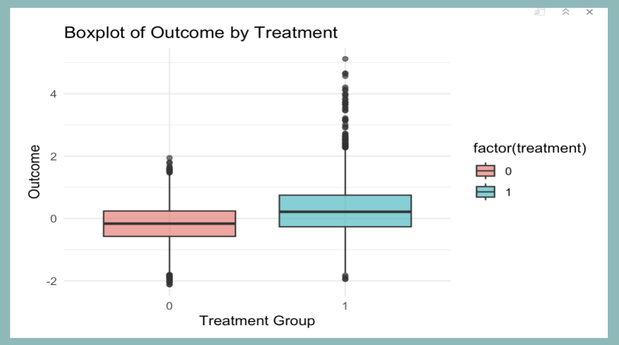
- Variable renaming for clarity (y → outcome, z → treatment).
- Basic group-wise summary statistics were computed to understand baseline differences in means and standard deviations between
- treated and control groups.

Exploratory Data Analysis (EDA):

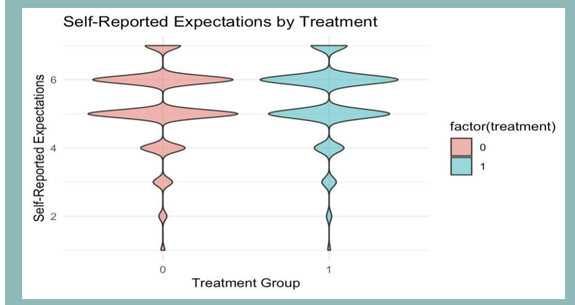
- **Histogram**: Visualized outcome distributions across treatment groups.
- **Boxplot**: Compared central tendency and dispersion of outcomes.
- **Violin Plot**: Assessed the distribution of self-reported expectations (mindset measures) between groups.
- **Bar Plot**: Examined gender distributions across treatment status.



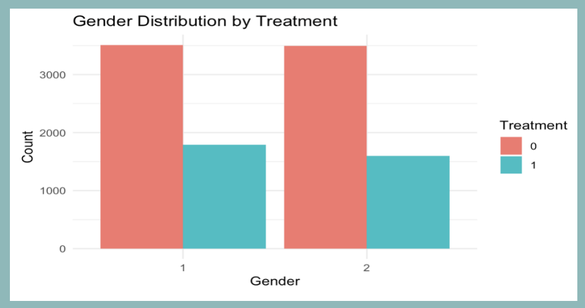
The histogram shows a rightward shift in the outcome distribution for the treated group, indicating that students who received the mindset intervention achieved higher academic scores.



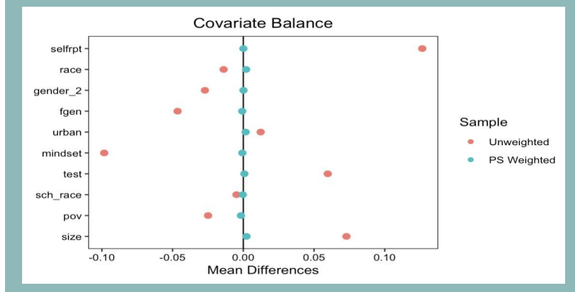
The treated group has a median outcome of approximately **0.3**, compared to **-0.1** in the control group, reflecting a shift of around **0.4 units**. The interquartile range (IQR) is also wider for the treated group (~1.5 vs. ~1.2),Indicating greater variability among high-performing students post-intervention.



The violin plot shows that students who received the mindset intervention (Treatment = 1) reported higher expectations on average, with a noticeable density peak around **6**, compared to the control group's peaks around **5–5.5**. This suggests the intervention not only influenced academic performance but also positively shifted students' internal beliefs about their potential.



The bar plot reveals a gender imbalance in treatment assignment: both male
(Gender = 1) and female (Gender = 2) students were more heavily represented in the control group than the treatment group. This imbalance underscores the need for covariate adjustment or matching to ensure that gender does not confound the estimated treatment effect.



The covariate balance plot demonstrates substantial imbalance across several covariates prior to matching, with standardized mean differences exceeding ±0.05 for variables such as selfrpt, test, and size. After applying propensity score weighting, all covariates moved close to zero, indicating successful covariate balance and enhancing the credibility of the estimated treatment effect.

RESULTS

Method	ATE (95% CI)
Unadjusted ATE	0.457 (0.426, 0.488)
Regression-Adjusted ATE	0.413 (0.388, 0.438)
IPW ATE	0.414 (0.379, 0.446)
AIPW ATE	0.412 (0.384, 0.440)

All four methods consistently estimate a positive and statistically significant impact of the mindset intervention on student achievement, with ATEs ranging from 0.412 to 0.457.

DISCUSSION AND DRAWBACKS

The mindset intervention demonstrated a consistent positive effect on student achievement, with ATE estimates ranging from **0.412 to 0.457** across all methods. These results suggest that such interventions can be a **scalable and cost-effective approach** to improving academic outcomes.
However, since this study used **observational data**, it may still be subject to **unmeasured confounding**. While methods like IPW and AIPW improved covariate balance, causal claims should be interpreted cautiously.
Additionally, the results reflect **short-term impacts**, and **generalizability** beyond the sample population is limited.

CONCLUSION

Our findings provide strong evidence that a growth mindset intervention can significantly improve student academic achievement. The consistency of results across multiple causal inference methods reinforces the **robustness of the estimated effect**. These insights support the potential for implementing mindset-based strategies as a **practical and scalable tool** in real-world educational settings.

REFERENCES

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