**Adapting Ed Tech Usage Recommendations to Enhance Academic Outcomes of Disadvantaged Students.**

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## Background

Prior research has observed that while most children experience some academic growth each school year, the scale of that yearly growth may be moderated by student classification (Nachazel, et al., 2018). English language learners (ELL), ethnic minorities, and students from families of low socioeconomic status have all been found to grow less in a school year compared to their peers (Gutman, Sameroff, and Cole, 2003; Kieffer, 2011; Nakamoto, Lindsey, and Manis, 2007). These differences in academic growth are often cited by school administrators as the rationale for implementing Education technologies (Ed Tech) in the classroom.

Ed Tech such as supplemental instructional software and digital texts are implemented in school districts across the nation as additional supports to level the field and close the gap for various student populations such as English language learners (ELL), ethnic minorities, or students of low socioeconomic status. While the implementation of Ed Tech programs has been found to be favorable for the improvement of English and math proficiency among K-12 children (Cheung & Slavin, 2012), these effects may vary across student demographic groups (Du et al., 2004).

One possible source for differences in Ed Tech efficacy may be the over or under utilization of Ed Tech by different student groups. In implementing a new Ed Tech program, many Ed Tech vendors provide school administrators with program usage recommendations (e.g., time in program) and suggested implementation strategies (e.g., station rotations). In employing these recommendations, educators assume that every student who uses the program at the recommended levels will achieve the maximum academic growth that the program can generate. However, student populations in most districts across the nation are anything but homogeneous. For example, nearly 20% of the K-12 student population in Texas is ELLs, over 60% are economically disadvantaged, and nearly 10% are enrolled in special education programs. Given this heterogeneity, administrators may need to question how they apply Ed Tech program usage recommendations to students of different demographic and socioeconomic categories. For some student populations such as ELLs, the effectiveness of supplemental Ed Tech programs such as the Imagine Math (IM) program by Imagine Learning may be enhanced and outcomes improved by increasing or decreasing usage above or below recommended levels.

## Research Questions

The objective of the study is to investigate whether mathematics achievement among various student demographic subpopulations may be optimized at different levels of Imagine Math usage. For this study, we chose to disaggregate mathematics score growth based on student ELL

status, disability status, economic disadvantage status, gender, and prior ability level. To meet these research goals the following questions were examined:

1. Is there an interaction effect between student demographic subgroup (ELL status, disability status, economic disadvantage status, gender and prior ability level) and Imagine Math usage level in estimating student mathematics score growth?
2. If interaction effects are observed, how does the association between Imagine Math usage and mathematics achievement differ by student demographic subgroup?

**Population**

The sample in this study was comprised of approximately 15,000 students from the state of Texas who were users of Imagine Math for grades 5 through 9. Fifty-one percent of the sample was male, 27 percent were classified as an ELL, 10 percent were classified as a student with a disability (learning or otherwise), and 88 percent qualified for free or reduced lunch.

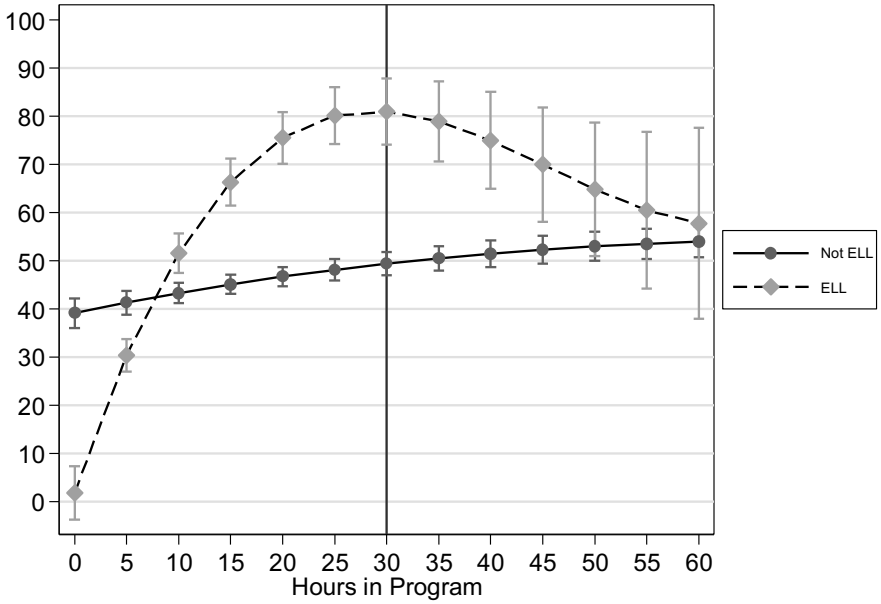
**Research Design**

Students' educational attainment in mathematics was measured with the State of Texas Assessments of Academic Readiness (STAAR) Mathematics assessment. The STAAR Mathematics assessment is administered annually to all students in the state of Texas in grades 3-8. The student demographic variables evaluated were English language learner (ELL) status, student disability status, economic disadvantage status (as determined by eligibility for free or reduce priced lunch), gender, and prior year STAAR performance level. The usage indicator was the number of hours students spent in the Imagine Math program for the 2018-2019 school year.

We used multiple linear regression to estimate the interaction between Imagine Math usage patterns and student demographic status. Specifically, separate models were computed for each possible Imagine Math usage and demographic interaction. Since we could not assume that the association between Imagine Math usage level and STAAR Mathematics performance was linear, we included Imagine Math usage level (number of hours) as a cubic factor so as to capture any changes in the direction and magnitude of the effect across different Imagine Math usage levels. By doing this, we could more definitively identify the optimal Imagine Math usage levels in the event that associations were indeed not linear. All demographic variables were included in each analytic model to account for potential confounding.

**Results and Conclusion**

Preliminary results indicated strong moderating effects of usage and demographic variables on average STAAR Mathematics performance growth. Generally, non-ELL and non-SPED students tended to experience greater STAAR Mathematics growth with increased Imagine Math usage. However, a pronounced curvilinear relationship between time in Imagine Math and STAAR Mathematics score growth was observed for ELL and SPED students. The relationship between time in program and STAAR Mathematics score growth did not vary significantly by economic disadvantage status, gender, or prior year STAAR Mathematics performance level. These findings present important implications for school administrators as they are considering the implementation of Ed Tech among various student populations within their educational agencies.




Note: Vertical line indicates Imagine Learning recommended usage level of 30 hours

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