The Impact of IXL on Academic Growth in Math and Reading: A Three-Wave Latent Growth Model

July 2023 | Xiaozhu An, Ph.D.

IXL is an end-to-end teaching and learning solution that engages learners in grades Pre-K through 12 with a comprehensive curriculum and personalized recommendations for meeting learning goals. Previous research has shown that IXL has a positive impact on students' academic performance (see https://www.ixl.com/research).

The present study adopted latent growth analysis to model grade 1-9 students' academic growth and examined the impact of IXL on learning trajectories of math and reading. Regardless of the different development dynamics observed in the two subjects, students with higher IXL usage exhibited faster academic growth compared to those with lower IXL usage in both math and reading.

Methodology

Participants

We studied a total of 6,595 students in grades 1 through 9 from 16 public schools in a large rural school district in South Carolina. Among them, 51% were boys, 68% qualified for free/reduced-price lunch, 20% were enrolled in special education programs, and 7% were English language learners (ELLs). In terms of race/ethnicity, the sample was 83% White, 8% Black, 6% Hispanic, and 3% other or mixed races.

DATA SOURCES

Academic Performance

We obtained the academic performance data from the school district. Students' academic performance was measured by the NWEA Measures of Academic Progress (MAP) assessments administered to students three times during the 2021-22 school year: beginning-of-year (September 2021), mid-year (December 2021), and end-of-year (April 2022).

Demographics

We also obtained student demographic background information from the district, including student grade level (i.e., grades 1 through 9), gender, race/ethnicity, English language learner (ELL) status, socioeconomic status (i.e., economically disadvantaged), and disability status (i.e., enrollment in special education programs).

IXL Usage

We retrieved students' IXL usage data from IXL's database. These data included IXL usage metrics throughout the 2021-22 school year, such as the number of questions answered on IXL, the amount of time spent on IXL, and the number of skills proficient (SP; i.e., skills in which students reached proficiency or a SmartScore of 80 or higher). The study used the averaged weekly number of SP (i.e., SP/week) as the main IXL usage metric. We excluded outliers (i.e., superusers) from analysis, leaving 6,195 students for math and 5,822 students for ELA.

ANALYSIS

We used the latent growth model (LGM) to construct students' continuous academic growth during one school year. For math and reading separately, we estimated two latent factors: the intercept (i.e., a student's initial assessment performance) and the slope (i.e., the growth rate of a student's assessment performance) with three waves of observed MAP assessments (in the 1st, 12th, and 29th weeks of the school year). A constant of 1 with freely-estimated paths pointing to the intercept and the slope was used to scale these latent factors and estimate their means. We freely estimated the correlation between the intercept and the slope factors. The loadings between the intercept factor and MAP assessments were all fixed to 1. The loadings between the slope factor and MAP assessments represent the linear trend of students' academic growth determined by the three-wave repeated measures (i.e., 0, 0.42, or 1 for assessment time 1, 2, and 3, respectively). Thus, the MAP score for student i at time t can be calculated as:

$$y_{it} = (1)*\alpha_i + \lambda_t*\beta_i + \varepsilon_{it}$$

Demographics were dummy coded and modeled as covariates predicting the intercept and the slope factors. Previous research reported weak positive correlations between academic performance and subsequent IXL usage (An et al., 2022), so we modeled a path from the intercept predicting IXL usage. To examine the effect of IXL on growth, we modeled a path from IXL usage predicting the slope.

Results

Math

The LGM for math demonstrated good model-data fit, with χ^2 = 700.645 (*df* = 35; *p* < .001), CFI = .982, RMSEA = .060, SRMR = .020 (see Figure A1 in Appendix). The average starting MAP math score was 212.27 (*p* < .001) with an average (yearly) growth rate of 8.89 (*p* < .001). There was a small positive correlation between the intercept and the slope factors (φ = 0.09, *p* < .001), indicating that students with higher initial MAP math scores grew faster throughout the school year. The intercept factor significantly predicted SP/week on IXL Math (*p* < .001), but the effect size was minimal (β = 0.01).

As hypothesized, SP/week significantly predicted the slope factor (*p* < .001) with an effect size of 0.18. This means that students with higher IXL Math usage grew faster than those with lower IXL Math usage. Specifically, for each additional SP/week on IXL Math, a student's yearly growth rate increased by 0.93 points.

Reading

Similarly, the LGM for reading showed good model fit, with χ^2 = 617.527 (*df* = 35; *p* < .001), CFI = .981, RMSEA = .056, SRMR = .019 (see Figure A2 in Appendix). The average starting MAP reading score was 211.91 (*p* < .001) with an average (yearly) growth rate of 6.23 (*p* < .001). There was a negative correlation between the intercept factor and the slope factor (φ = -0.30, *p* < .001), indicating that students with lower initial MAP reading scores grew faster across the school year. Different from what we observed for math, the intercept factor negatively predicted SP/week on IXL ELA (*p* < .001; β = -0.10), which means that students who started with lower MAP reading scores tended to use IXL ELA more.

Consistent with our hypothesis, SP/week significantly predicted the slope factor (*p* < .001) with an effect size of 0.18. This means that students with higher IXL ELA usage grew faster than their peers with lower IXL ELA usage. Specifically, for each additional SP/week on IXL ELA, a student's yearly growth rate increased by 1.41 points.

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[1] *α_i : student i's initial MAP score (i.e., baseline at the beginning of the school year);*
λ_t : time-varying loading vector (i.e., 0, 0.42, or 1);
β_i : slope factor for student i (i.e., student i's growth rate on MAP);
ε_{it} : error term.

[2] *CFI values equal to or above .95, and RMSEA and SRMR values equal to or below .08 were considered indicative of satisfactory model-data fit (Hu & Bentler, 1999). CFI = comparative fit index; RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual.*

[3] *For research in the education field, effect sizes between 0.05 and 0.20 would be considered medium, and effect sizes of 0.20 or higher would be considered quite large (Kraft, 2020; Lipsey et al., 2012).*

Conclusion

As expected, students with more IXL usage exhibited faster academic growth compared to their peers with lower IXL usage. The effect sizes of IXL's impact on both math and reading were moderate, even though IXL usage of the sample (M_{SP} = 1.28 for IXL Math and M_{SP} = 0.73 for IXL ELA) fell short of IXL's recommendation for reaching proficiency in two or more skills per week. Increased IXL usage is likely to result in even greater effect sizes (Noell et al., 2002).

Interestingly, different development dynamics were observed in math and reading. In the model for math, students who initially performed better grew faster across the school year. In contrast, this correlation was negative for reading. Previous studies have also observed similar trajectories for math (e.g., Aunola et al., 2004) and reading (e.g., Debatin, 2019). A plausible explanation lies in the different learning progressions of the two subjects. Math concepts build on each other, requiring a solid foundation and understanding before new concepts are introduced. As such, a student's initial math knowledge is critical for later growth. ELA, however, does not work this way, as the concepts and skills are more independent from each other. Consequently, a student who begins the school year with relatively low performance in reading would have more room to grow with effective learning tools like IXL.

References

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Peer Review: *This study was peer reviewed and presented at the 2024 Annual Meeting of the American Educational Research Association in Philadelphia, PA.*

Appendix. Latent Growth Models

Figure A1. LGM for Math[4]

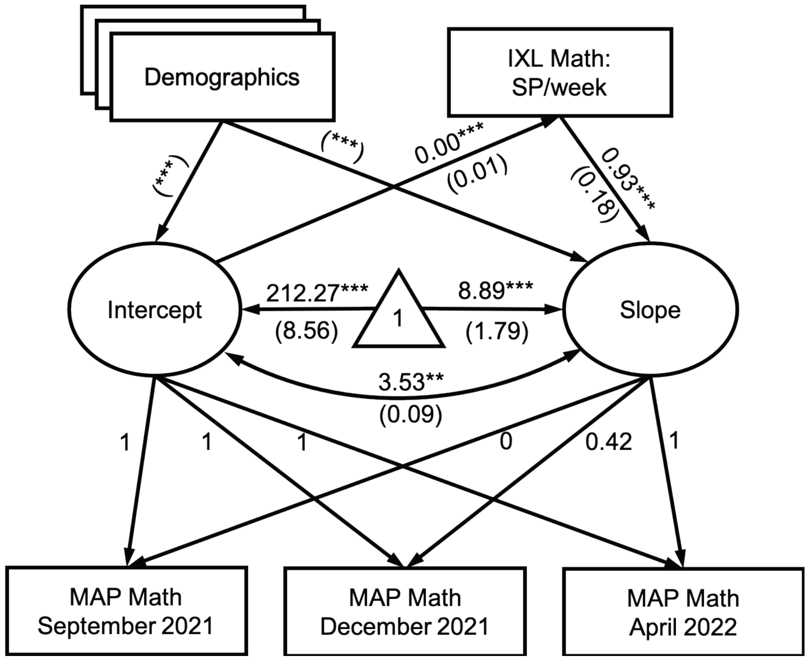
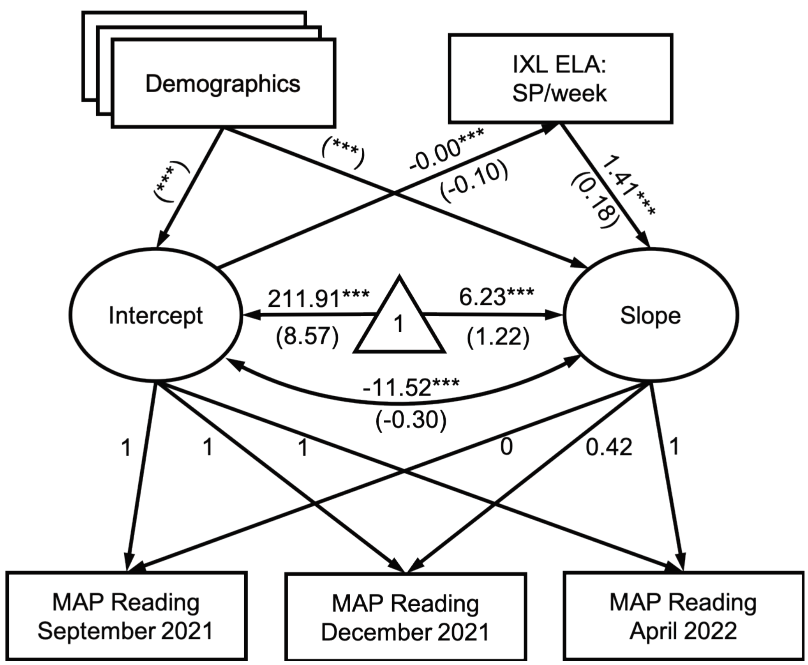


Figure A2. LGM for Reading



[4] *Unstandardized regression coefficients are presented above the path with standardized regression coefficients below the path in parentheses; * significant at .05; ** significant at .01; *** significant at .001.*