

## Growth in Reading Ability as a Response to Using EdSphere™

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### OBJECTIVE

Educators are aggressively working to implement the Common Core State Standards (CCSS). Student use of technology is one potential key to helping students meet higher reading standards proposed by the CCSS (National Education Technology Plan, 2010). Well-designed technology includes components of deliberate practice. Research (Glaser, 1996; Kellogg, 2006; Shea & Paull, 1996; Wagner & Stanovich, 1996) suggests that a novice develops into an expert through an intricate process that includes the following components: (a) targeted practice in which each person is engaged in developmentally appropriate activities; (b) real-time scoring and corrective feedback that is based on each person's performance; (c) intensive practice on a daily basis that provides results to monitor contemporaneous ability; (d) distributed practice that provides appropriate activities over a long period of time (e.g., 5–10 years, 10,000 hours), which allows for monitoring growth towards expert performance; and (e) self-directed practice when a coach, teacher, or mentor is not available. Students benefit from these components of deliberate practice when their day-to-day and year-to-year performance is placed on an equal-interval developmental scale. This essential component allows for monitoring status and growth in response to deliberate practice.

EdSphere™, formerly known as Learning Oasis™ (Hanlon, Swartz, Stenner, Burdick, & Burdick, 2012) is a web-based application that leverages the ability of The Lexile® Framework for Reading and The Lexile® Framework for Writing to provide students with activities targeted to their abilities and to topics being taught in the classroom. One of the most important features of this application is that each student's reading ability is monitored using auto-generated cloze items that students answer while reading, and writing ability is monitored using a wide variety of prompts and paragraphs that require editing by students. The auto-scoring features in EdSphere provide each student with immediate feedback about his or her performance in each area (e.g., time spent reading and writing, amount of words read and written, and percent correct). Each student's performance is used to immediately update the estimate of his or her ability. Students can watch their ability grow over time with the reports that are included in every student's digital portfolio. Educators can be confident about the precision and utility of each student's measure of ability, and they avoid sacrificing more instructional time for testing.

The objective of this research was to ascertain whether student growth in reading in response to exposure to EdSphere could be determined from an external progress-monitoring measure. Two alternate methodologies are applied to longitudinal data from a panel of students who encountered EdSphere in the fall of seventh grade to detect evidence that EdSphere usage is reflected in the reading achievement scores. Exposure is operationalized in two ways: (a) through a time-varying dosage variable (i.e., cumulative reading encounters using EdSphere determined at each occasion of measurement); and, (b) through a time-invariant dosage variable (i.e., total cumulative reading encounters using EdSphere).

### Key Hypotheses:

There are two key hypotheses:

- 1) Student reading ability increases over time with EdSphere usage; and,
- 2) Changes in the velocity and acceleration of the average student growth curve are coincident with EdSphere exposure.

Appropriate null hypotheses are identified for each analysis. However, statistical tests for parameter estimates are not consistently implemented in software for the multilevel framework (and sometimes are not implemented at all). Therefore p-values, when available, are regarded as suggestive rather than the final word on the significance of the effects. We regard the consistency of the findings from the alternate analyses as more compelling evidence.

### METHODS

#### Participants:

Participants constituted a panel of students (n = 392) who attended a large middle school in the southeastern United States as eighth-graders in 2010-11 and had historical reading data spanning grades 2-8. Approximately 50% of the students were Caucasian, 43% African-American, 4% Asian, 2% Asian-American, and less than 0.5% Latino. Students began using EdSphere in the winter of 2009-10 (their seventh-grade year).

#### Procedure:

The longitudinal reading data were analyzed in three phases. In the first phase, Gierada and Berger (2012) analyzed individual student's scores with a mixed model that estimated the parameters of a quadratic growth trajectory and a single time-varying dosage variable as a predictor of student performance on each occasion. In the second phase, we generalized a discontinuous growth model explicated by Singer and Willett (2003) and used it to detect possible effects on the parameters of growth at the point of discontinuity (onset of EdSphere usage) and during the exposure period of fifteen months. These two model formulations provide alternate interpretations of how exposure to EdSphere could be manifested in student growth. In the third phase of the study, a growth model was fit to the historical data collected prior to the onset of EdSphere to provide a counterfactual growth estimate. The results for each model were interpreted; and, the total growth during the exposure period was compared under the alternate model formulations and the counterfactual.

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### Measures:

The Northwest Evaluation Association (NWEA) Measures of Academic Progress® (MAP®) were used to produce student scores in reading on each measurement occasion. The MAP yields reading measures (Lexile® measures) derived from the Lexile Framework for Reading. Lexile measures (Stenner, Burdick, Sanford & Burdick, 2007) are measures of reader ability and text complexity that are based on semantic and syntactic factors and are reported on a developmental scale. Independent psychometric studies of the Lexile scale (Mesmer, 2007; White & Clement, 2001) indicate that it is a valid and reliable measure of reader ability and text complexity.

A Lexile measure is the numeric representation of an individual's reading ability or a text's complexity (or, difficulty), followed by an "L" (for Lexile). The Lexile scale ranges from 0L and below for emerging readers and beginning texts to above 1600L for advanced readers and texts. Values at or below 0L are reported as "Beginning Reader" (BR).

Extensive information about the development of the Lexile Framework can be found in the "Researchers" section of the Lexile website ([www.Lexile.com](http://www.Lexile.com)).

The cumulative number of encounters in EdSphere is a variable that tracks how many reading passages a student reads and responds to during his or her use of EdSphere. This variable may be thought of as a "dosage" or "exposure" variable that quantifies the degree to which a student engages with targeted reading practice as implemented by EdSphere (Hanlon, 2012).

### ANALYSES

In all, four models were fit to the data. Each is explained in this section. First, we establish some notation. We let

$L_{ij}$  = the Lexile measure from the NWEA MAP for student  $i$  on occasion  $j$ ;

$t_j$  = for each occasion  $j$ , the months since initial measurement (i.e., fall of second grade; or, September 2004), centered at the initial occasion; and,

$D_i(t_j)$  = the cumulative number of "encounters" with EdSphere for student  $i$  at month  $t_j$  (it equals zero through month 63 when initial exposure began).

The first model, which we call Model A, is summarized from Gierada and Berger (2012). In their formulation, they used a mixed model that expressed the student's score as a function of a quadratic growth curve and a time-varying covariate (i.e., cumulative number of encounters at occasion  $j$ ). We have altered their notation so as to maintain a consistent notation within this research brief. Acknowledging that change, Gierada and Berger's model was expressed by them as follows.

#### Model A

$$L_{ij} = [1, t_j, t_j^2, D_i(t_j)]\boldsymbol{\theta} + [1, t_j, t_j^2, D_i(t_j)]\boldsymbol{\lambda}_i + \epsilon_{ij}$$

where we assume that  $\epsilon_{ij} \sim N(0, \sigma^2)$ ; and,  $\boldsymbol{\lambda}_i = [\lambda_{0i}, \lambda_{1i}, \lambda_{2i}, \lambda_{3i}]^T \sim MVN(\mathbf{0}, \mathbf{A})$ . We find it useful to re-express their model in a multilevel formulation to facilitate comparison of this model with the subsequent models that we utilize. Thus Model A can also be written:

#### Level 1:

$$L_{ij} = \beta_{0i} + \beta_{1i}t_j + \beta_{2i}t_j^2 + \beta_{3i}D_i(t_j) + \epsilon_{ij}$$

#### Level 2:

$$\begin{aligned}\beta_{0i} &= \theta_0 + \lambda_{0i} \\ \beta_{1i} &= \theta_1 + \lambda_{1i} \\ \beta_{2i} &= \theta_2 + \lambda_{2i} \\ \beta_{3i} &= \theta_3 + \lambda_{3i}\end{aligned}$$

Note that  $D_i(t_j)$  is a within-person (Level 1) time-varying covariate in this model formulation. The coefficient  $\theta_3$  expresses the change in average Lexile measure that is associated with an increase of one encounter with EdSphere, *in addition to* the improvement predicted by the average growth curve. The null hypothesis of central interest in this model would classically be  $H_0: \theta_3 = 0$  versus the alternative,  $H_a: \theta_3 \neq 0$ . However, Gierada and Berger used a Bayesian analysis rather than a classical statistical analysis and so they provided a 95% posterior interval instead. Their findings are summarized in the Results section.

It is important to note that measurement occasions occurred three times per year: September, December and March. Taking September 2004 (the time when the participants entered the second grade) as the origin of the time scale, the time-scale is appropriately coded so that the occasions of measurement are:  $t_j = 0, 3, 6, 12, 15, 18, \dots, 60, 63, 66, 72, 75, 78$ . Thus, in Gierada and Berger's model,  $\theta_0$  is the average Lexile measure for the group of participants in September 2004 just as they were entering second grade;  $\theta_1$  is the instantaneous velocity of growth in the average growth curve in September 2004; and,  $2\theta_2$  is the (constant) acceleration rate of the average quadratic growth curve. EdSphere was

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introduced to the eighth-grade panel at  $t_j = 63$ , which corresponds to the winter of their seventh-grade year. The parameter  $\theta_3$  indicates the increase in the average reading ability that is associated with a one-unit (one encounter) increase in  $D_i(t_j)$  from month 63 onward. Thus  $\theta_3$  reflects an increase in average performance beyond that accounted for by growth.

Model A does not readily enable us to characterize the impact that targeted practice may have on an individual's overall growth curve—i.e., its effect on the *parameters* of growth. For that we turn to Models B and C.

### Model B (Discontinuous Quadratic Growth)

Model B is a generalization of the discontinuous straight-line growth model explicated by Singer and Willett (2003, pp. 195-198). Their model was designed to detect an increment to the slope (growth rate) of a straight-line growth model coincident with a point of discontinuity associated with the attainment of an educational credential. As we are interested in curvilinear growth, it was necessary to extend their model formulation to detect effects on the velocity and acceleration of growth associated with exposure to EdSphere. To do that, we define two auxiliary time-scales and expand the multilevel model to accommodate curvilinear (quadratic) growth during two time-frames: the period prior to exposure to EdSphere; and, the period of exposure to EdSphere.

First, we re-center the original time scale by defining  $T_j = (t_j - 63)$ . This places the origin of the new time scale at the point of discontinuity—i.e., the point at which EdSphere was introduced. Secondly, we define a second time variable to partition the total time frame into two parts. To do that we let

$$E_j = \begin{cases} 0 & \text{if } t_j < 63 \\ T_j & \text{if } t_j \geq 63 \end{cases}$$

Note that from month 63 on to the last occasion of measurement,  $T_j$  and  $E_j$  are precisely synchronized in their cadence, as prescribed by Singer and Willett (2003). Synchronizing and centering the two time variables this way allows the model parameters to be interpreted in terms that are directly related to the second hypothesis of interest. This is apparent from the following multilevel formulation.

#### Level 1

$$L_{ij} = \pi_{0i} + \pi_{1i}T_j + \pi_{2i}T_j^2 + \pi_{3i}E_j + \pi_{4i}E_j^2 + \varepsilon_{ij}$$

#### Level 2

$$\pi_{0i} = \gamma_{00} + r_{0i}$$

$$\pi_{1i} = \gamma_{10} + r_{1i}$$

$$\pi_{2i} = \gamma_{20} + r_{2i}$$

$$\pi_{3i} = \gamma_{30} + r_{3i}$$

$$\pi_{4i} = \gamma_{40} + r_{4i}$$

In this model,  $\gamma_{00}$  represents the average Lexile measure in month 63 (when  $T_j = E_j = 0$ ). Similarly,  $\gamma_{10}$  is the instantaneous velocity of growth at month 63 and  $2\gamma_{20}$  is the acceleration rate at month 63. The parameter  $\gamma_{30}$  represents the increment to the instantaneous velocity of growth at the onset of EdSphere;  $\gamma_{10} + \gamma_{30}$  is the new velocity associated with the introduction of EdSphere. Similarly, the model represents the potential impact of EdSphere on the acceleration of growth at month 63 in the curvature parameter,  $\gamma_{40}$ , the new acceleration being  $2(\gamma_{20} + \gamma_{40})$ . (Note: In the quadratic growth model, acceleration is equal to two times the curvature parameter.) The null hypothesis of interest in this model is  $H_0: \gamma_{30} = \gamma_{40} = 0$  versus the alternative,  $H_a: \gamma_{30} \neq 0$  and/or  $\gamma_{40} \neq 0$ . Note that this model reflects the potential influence of EdSphere on the average growth curve without explicitly modeling the role of the dosage variable. Rejection of the null hypothesis is sufficient to support the claim that using EdSphere impacts either the velocity or the acceleration of growth, or both.

### Model C (Discontinuous Quadratic Growth with Time-Invariant Dosage Variable)

#### Level 1

$$L_{ij} = \pi_{0i} + \pi_{1i}T_j + \pi_{2i}T_j^2 + \pi_{3i}E_j + \pi_{4i}E_j^2 + \varepsilon_{ij}$$

#### Level 2

$$\pi_{0i} = \gamma_{00} + r_{0i}$$

$$\pi_{1i} = \gamma_{10} + r_{1i}$$

$$\pi_{2i} = \gamma_{20} + r_{2i}$$

$$\pi_{3i} = \gamma_{30} + \gamma_{31}D_i(78) + r_{3i}$$

$$\pi_{4i} = \gamma_{40} + \gamma_{41}D_i(78) + r_{4i}$$

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In Level 1, Model C is identical to Model B. The difference between the models lies in Level 2, where we have incorporated the total cumulative number of encounters for person  $i$  on the final occasion of measurement (month 78) as a predictor of the increments to velocity and acceleration. We envision that total usage may influence the growth curve during the exposure period. The predictor  $D_i(78)$  is thus a time-invariant predictor of the parameters of individual growth in this formulation. The classical null hypothesis of interest would be  $H_0: \gamma_{30} = \gamma_{31} = \gamma_{40} = \gamma_{41} = 0$  versus the alternative that one or more of the designated parameters are different from zero.

### Model D (Counterfactual)

Models A, B and C each provide possible counterfactuals for the growth under the conditions that EdSphere had not been implemented (simply set the dosage variable to zero). However, the growth curves so derived are influenced by the data in months 63-78 and do not truly reflect a non-usage condition. To arrive at a more desirable counterfactual for growth, we fit a quadratic growth model that is not influenced by the data during the time of exposure. Thus the model was fit to the data for  $t_j = 0, \dots, 63$ . So the parameters reflect student growth totally uninfluenced by exposure to EdSphere.

### Level 1

$$L_{ij} = \pi_{0i} + \pi_{1i}t_j + \pi_{2i}t_j^2 + \varepsilon_{ij}$$

### Level 2

$$\pi_{0i} = \gamma_{00} + r_{0i}$$

$$\pi_{1i} = \gamma_{10} + r_{1i}$$

$$\pi_{2i} = \gamma_{20} + r_{2i}$$

The gamma terms have the usual interpretations in terms of status, instantaneous velocity of growth and acceleration. Our primary use of this model will be in providing an estimate of final status and total gain during the time of exposure under the counterfactual condition that EdSphere had not been implemented.

The results are presented in the next section.

## RESULTS & DISCUSSION

Gierada and Berger (2012) provided the results for Model A. They found that

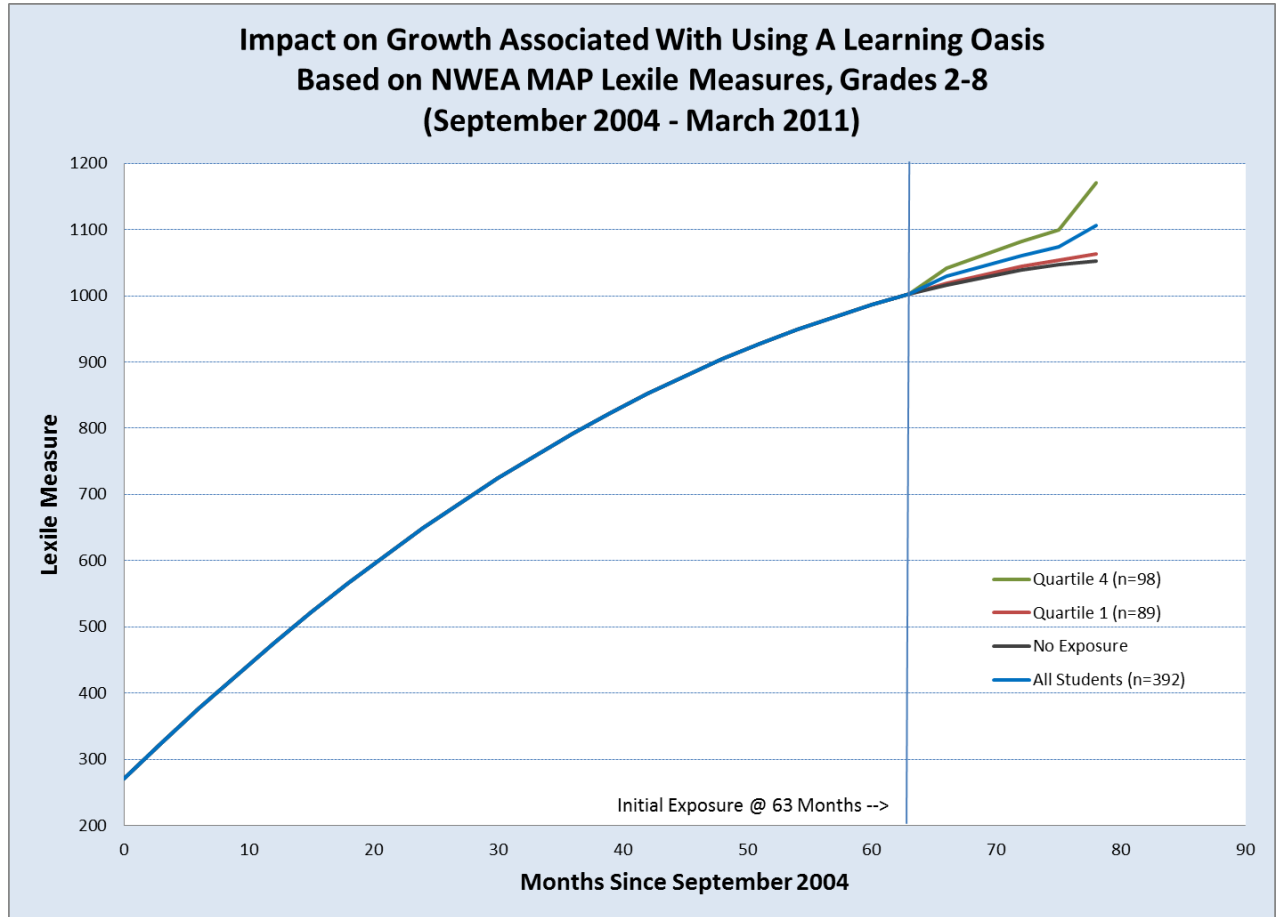
$$\hat{\theta} = \begin{pmatrix} \hat{\theta}_0 \\ \hat{\theta}_1 \\ \hat{\theta}_2 \\ \hat{\theta}_3 \end{pmatrix} = \begin{pmatrix} 270.59 \\ 18.30 \\ -0.106 \\ 1.062 \end{pmatrix}$$

As they used a Bayesian estimation procedure (i.e., MCMCPack in R), they gave the 95% posterior interval for  $\hat{\theta}_3$  as (0.947, 1.18). This supports the conclusion that reading ability increased approximately 1L (one Lexile) beyond normal growth for every encounter with EdSphere.

We visualize this result in Figure 1 by positing different dosage trajectories and calculating the predicted values,  $\hat{L}_{ij}$  for each dosage. For the figure, we calculated the average dosage trajectory for the entire group of 392 students by calculating the average of the cumulative number of encounters at each measurement occasion. We also depict a “low exposure” group by calculating the average dosage trajectory for students whose total usage was in the bottom quartile (Q1) for the total sample. Similarly, we produced a “high exposure” group by calculating the average dosage trajectory for students whose total cumulative encounters were in the top quartile (Q4) for the total sample.

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Figure 1. Graphical Depiction of Model A



The results for Models B through D are shown in Table 1.

Table 1. Summary of Fixed Effects Estimates for Models B through D

Parameter	Model B (Discontinuous Growth)	Model C (Discontinuous Growth, Dosage)	Model D (Counterfactual Growth)
$\gamma_{00}$ (Intercept)	999.8	999.8	268.8
$\gamma_{10}$ (Velocity)	4.5	4.5	19.1
$\gamma_{20}$ (Curvature <sup>1</sup> )	-0.12	-0.12	-0.12
$\gamma_{30}$ (Increment to velocity)	0.27 *	1.64 *	--
$\gamma_{31}$ (Dosage effect: velocity)	--	-0.03 *	--
$\gamma_{40}$ (Increment to curvature)	0.28	0.16 *	--
$\gamma_{41}$ (Dosage effect: curvature)	--	0.002 *	--
$\gamma_{10} + \gamma_{30}$	4.8	--	--
$\gamma_{20} + \gamma_{40}$	0.16	--	--
$\gamma_{10} + \gamma_{30} + \gamma_{31}\bar{D}_i(78)$	--	4.8	--
$\gamma_{20} + \gamma_{40} + \gamma_{41}\bar{D}_i(78)$	--	0.16	--

\* Not statistically significant based on output from LME module in R

<sup>1</sup> In a quadratic growth model the acceleration is given by multiplying the curvature parameter by 2.

The results for Model B indicate that the observed positive increment to velocity is not statistically significant while the increment to curvature is significantly different from zero. Therefore the null hypothesis that EdSphere has no effect on either velocity or curvature can be rejected. Taking into account that p-values for multilevel models are not consistently implemented (e.g., the LME module of R provides them while the LMER module does not) the observed increase in velocity (4.5 to 4.8) could still be suggestive. In any case, the impact on acceleration appears

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to be statistically significant and also substantively notable because it indicates that on average decelerating growth has been replaced by accelerating growth.

The results for Model C fail to produce statistically significant effects on velocity or growth based on LME output. Thus, the classical null hypothesis cannot be rejected. However, the model provides estimates of velocity and acceleration after exposure that are identical to those provided by Model B (note the shaded cells in the table). The two views are consistent with each other and with the results of Model A, especially when viewed in light of the estimated total gain in reading ability during the 15-month exposure period (Table 2). Perhaps even more importantly, Table 2 confirms that Model A, Model B and Model C all support the inference that during the exposure period students using EdSphere experienced three times the total gain that would have been expected based on the growth exhibited prior to the onset of EdSphere.

**Table 2. Consistency of Models and Total Estimated Gain Versus Counterfactual Gain**

	Model A Gierada & Berger	Model B Discontinuous Quadratic Growth	Model C Incorporate Dosage into Model B	Model D Counterfactual
Predicted (63)	1003L	1000L	1000L	997L
Predicted (78)	1106L	1107L	1107L	1030L
Total Gain	103L	107L	107L	33L

Based on this collection of results there appears to be evidence to support the two key hypotheses stated at the beginning of this research brief. At the very least, these results suggest that research on the efficacy of EdSphere for improving reading ability deserves further attention and replication.

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