



Making Real-World Decisions about Adequate Progress: Comparing Three Approaches or “Now I Have More Questions than Answers”

Roland H. Good III, Ph.D.
Kelly A. Powell-Smith, Ph.D., NCSP
Elizabeth N. Dewey, M.S.
Dynamic Measurement Group, Inc.

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Disclosure

Roland Good is a co-owner of Dynamic Measurement Group, Inc. (DMG).
Kelly Powell-Smith is an employee of DMG.

DMG is an educational company that is dedicated to supporting success for children and schools. DMG was founded by Roland H. Good III and Ruth Kaminski, authors of the Dynamic Indicators of Basic Early Literacy Skills (DIBELS®), and is the official home of DIBELS research, development, and training.

DMG receives revenue from the publication of DIBELS® assessments, training and professional development, and the operation of the DIBELSnet® data reporting service.

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Agenda

- Rationale for & importance of progress monitoring
- Desirable qualities of progress monitoring
- Metrics used to evaluate progress
- Purpose & research questions
- Procedures
- Results
- Discussion & Questions

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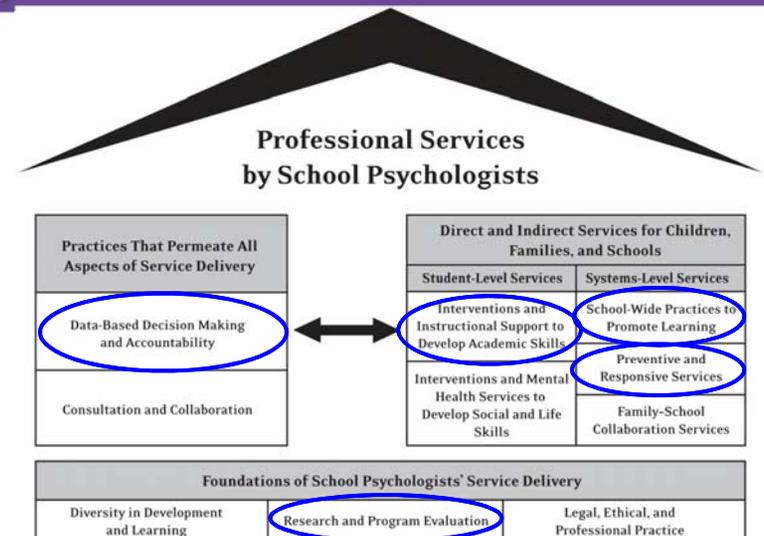
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NASP Practice Model



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Essential Elements of RTI

Although there is no specific definition of RTI, essential elements can be found when we take a look at how states, schools, and districts fit RTI into their work. In general, RTI includes:

- ▶ screening children within the general curriculum,
- ▶ tiered instruction of **increasing intensity**,
- ▶ evidence-based **instruction**,
- ▶ close **monitoring of student progress**, and
- ▶ informed **decision making** regarding next steps for individual students.

<http://www.parentcenterhub.org/repository/rti/#elements>

Accessed: 2/19/2017

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What is progress monitoring and formative evaluation?

To implement progress monitoring, the student's **current levels of performance** are determined and **goals are identified** for learning that will take place over time. The student's academic performance is **measured on a regular basis (weekly or monthly)**. Progress toward meeting the student's goals is measured by **comparing expected and actual rates of learning**. Based on these measurements, **teaching is adjusted** as needed. Thus, the student's progression of achievement is monitored and instructional techniques are adjusted to meet the individual students learning needs.

<http://www.studentprogress.org/progresmon.asp#2>

Accessed: 1/22/2015

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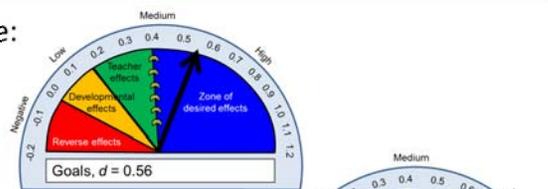
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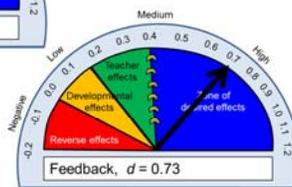
Selected Hattie (2009) Findings...

Desirable *Goals* are:

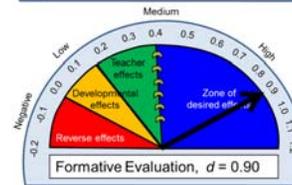
Meaningful,
Attainable,
Ambitious



Feedback to teachers & students: Is what we are doing working?



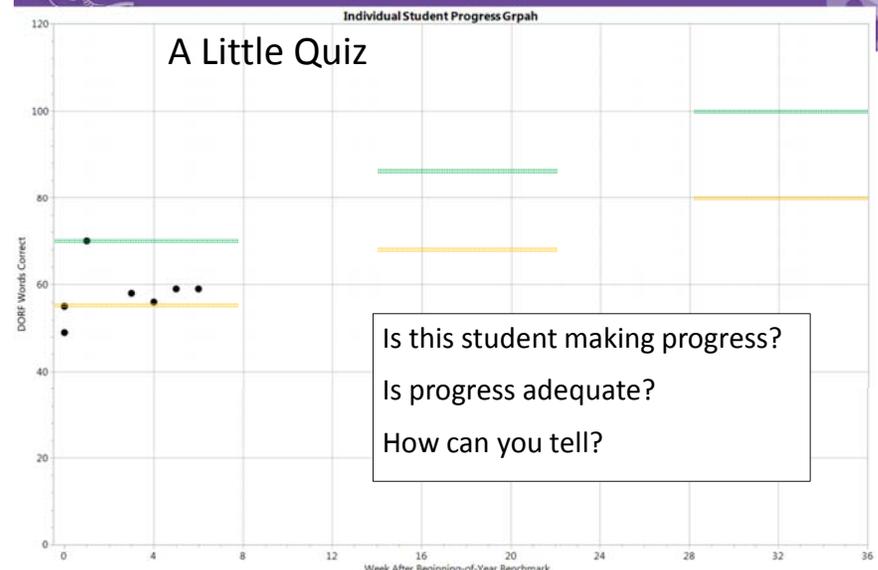
Progress Monitoring and Formative evaluation is the 3rd largest effect on student achievement out of 138 possible influences.



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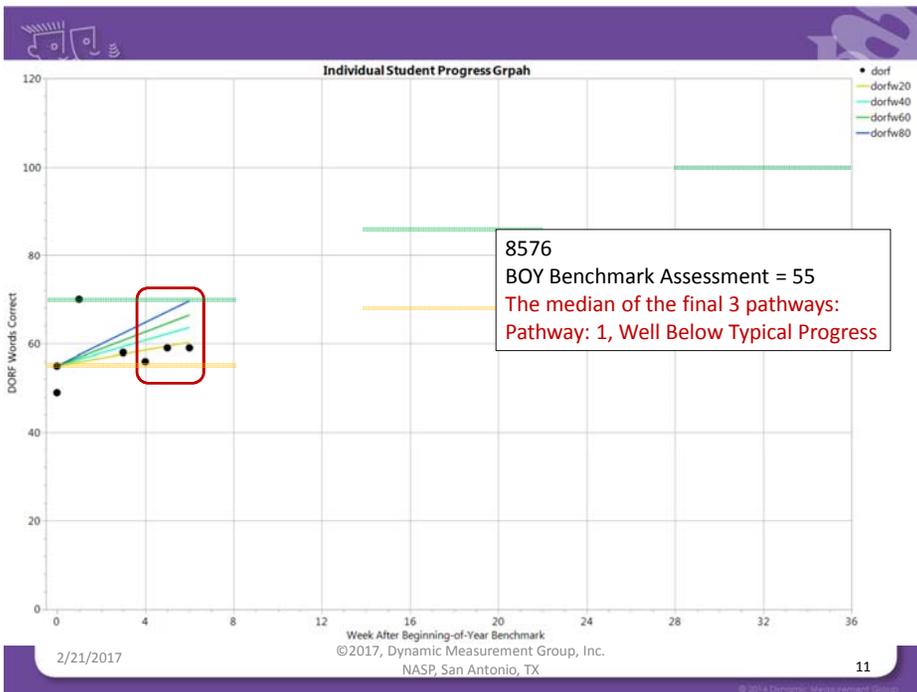
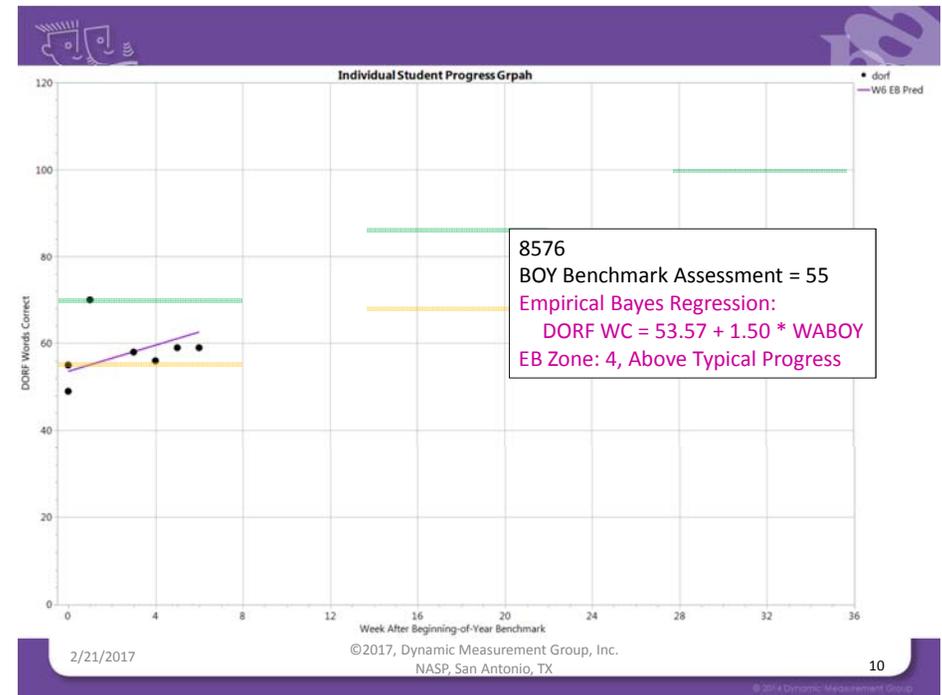
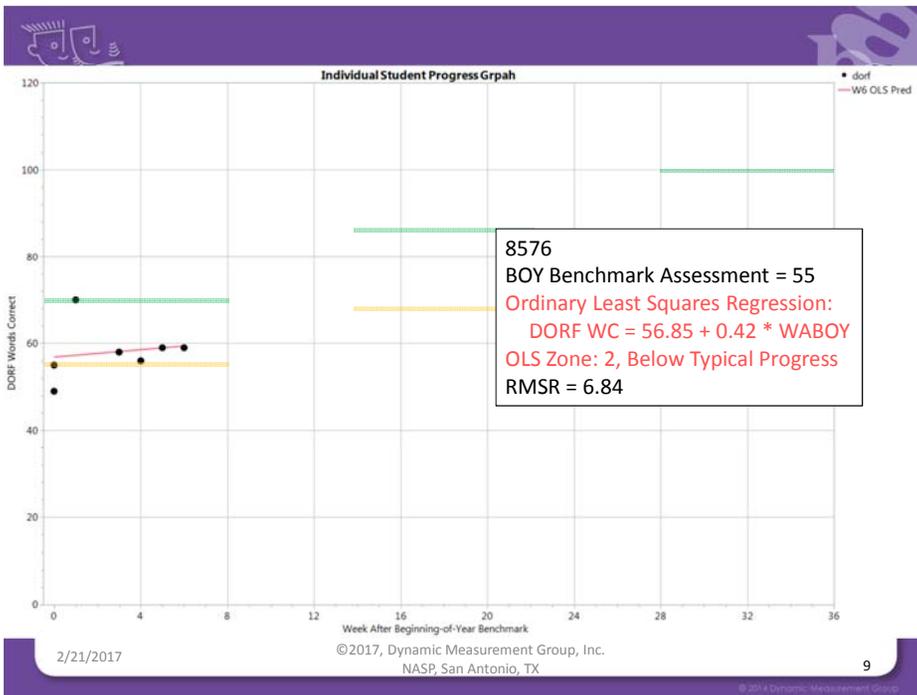
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Good Progress Monitoring Decisions

Good progress monitoring decisions are ones that enable educators to improve outcomes for students.

1. Good decisions about progress provide **timely** information to inform instruction.
 - Can we make a decision in 6 weeks?
2. Good decisions about progress are reasonably **stable** and reliable.
 - Would we make the same decision next week?
3. Good decisions about progress provide **instructionally relevant** information for individual students.
 - Does the progress decision inform outcomes?

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Methods/Metrics for Evaluating Progress

1. Scatter plot (with/without aimline)
2. Scatter plot with aimline & 3 – 5 data point rule
3. Scatter plot with aimline & trendline/slope
4. *Slope* with ROI norms
 - 4a. Ordinary Least Squares (OLS)
 - 4b. Empirical Bayes (EB)
5. *Level of student skills at a point in time* with Pathways of Progress

**Focus
for
today**

What have you seen commonly used in practice?

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Concerns with Slope

- Reliability of slope at the individual student level has been questioned
 - Good (2009) found estimates of .64 with 16 data points over a 5 month period
 - When the sample was restricted to include only students with RMSE below 10.36, reliability increased to .78
 - Thornblad & Christ (2014) found reliability ranged from .21 at two weeks to .61 at 6 weeks. Even with daily monitoring over 6 weeks, the reliability of slope was only .61.

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Concerns with Slope

- Length of time and number of data points needed to achieve a stable slope is of concern for practical reasons.
 - Early work argued for at least 10 data points (Gall & Gall, 2007; Good & Shinn, 1990; Parker, Tindal, & Stein, 1992; Shinn, 2002).
 - Christ (2006) argued for a minimum of 2 data points per week for 10 weeks for low-stakes decisions, more for high-stakes decisions.
- If even minimally stable decisions about progress can only be made after three or more months of data collection, such decisions may be of too little practical benefit.

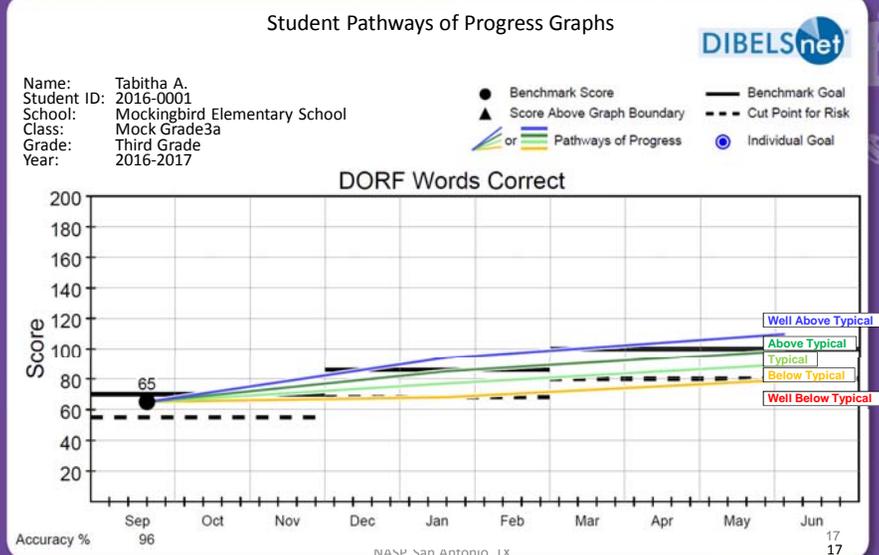
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Alternative: Pathways of Progress





Purpose of Pathways of Progress™

- Assist in setting **ambitious, meaningful, attainable** student learning goals and evaluating progress.
- Provide a normative reference to consider when setting goals and evaluating progress.
- Clarify what rate of progress is typical, above typical, well above typical, as well as below typical or well-below typical.



Another Approach: Empirical Bayes Slope

Recently examined by Christ, Newell, & Musgrove (2016).

- Simulation design
- Expert versus novice acceptability; examined decisions at 6 weeks and 20 weeks.

Empirical Bayes Slope for individual i , b_{1i}^* :

$$b_{1i}^* = \lambda_{1i} \hat{b}_{ti} + (1 - \lambda_{1i}) \hat{\beta}_{11}$$

\hat{b}_{ij} is the OLS estimate of the slope of individual i based on that person's data;

$\hat{\beta}_{11}$ is the estimate of the grand mean slope;

λ_{1i} is the reliability for individual i .

Christ, Newell, & Musgrove (2016)



Conceptual Attractiveness of

Empirical Bayes $b_{1i}^* = \lambda_{1i} \hat{b}_{ti} + (1 - \lambda_{1i}) \hat{\beta}_{11}$

In this study, the estimate of the grand mean slope ($\hat{\beta}_{11}$) is 1.408

- In the case where the reliability of the OLS slope for an individual student is perfect (i.e., $\lambda_{1i} = 1$) then the Empirical Bayes estimate of slope should be equal to the OLS slope (\hat{b}_{ti}).
- In the case where the OLS slope for an individual student has 0 reliability (i.e., $\lambda_{1i} = 0$) then the Empirical Bayes estimate of slope should be equal to the grand mean slope ($\hat{\beta}_{11} = 1.408$).
- Conceptually, the Empirical Bayes slope estimate should fall between the OLS slope and the grand mean slope, and be closer to the grand mean slope as the reliability of the individual slope estimate decreases.



Purpose

The purpose of this study is to compare three different approaches to evaluating student progress.

- Ordinary Least Squares (OLS) slope with respect to ROI norms
- Empirical Bayes (EB) slope with respect to ROI norms
- Pathways of Progress median of last 3 pathways



Research Questions

Research questions include:

1. What is the reliability of each approach?
2. What is the validity of each approach?
3. What is the utility of each approach?



Apples to Apples Comparison

This study was designed with the primary goal of conducting an apples-to-apples-apples comparison of (a) OLS slope with ROI band, (b) EB slope with ROI band, and (c) level of performance with Pathways of Progress.

1. The same participants were used for all metrics.
2. The same scores were used for decisions.
3. The same procedure was used to estimate the reliability of the student measure.
4. The same basis was used to make a progress decision:

Below 20th	20 th to 40 th	40 th to 60 th	60 th to 80 th	Above 80 th
Well Below	Below	Typical	Above	Well Above



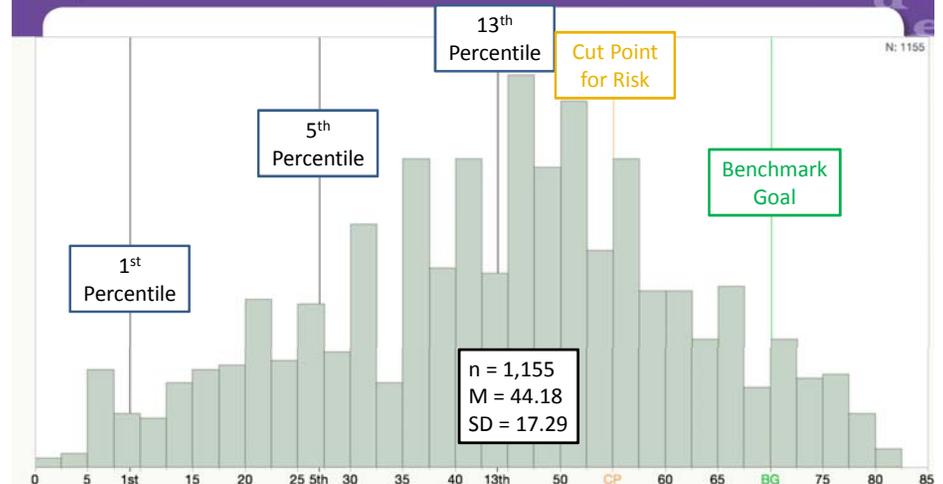
Methodology: Participants

Participants included 1155 third-grade students in DIBELSnet data systems who met the following criteria...

- ✓ tested with DIBELS Next® during the 2014-2015 academic year
- ✓ data entered into the DIBELSnet® or Amplify mCLASS data management systems
- ✓ had 6 – 8 DORF Words Correct data points within the first 6 weeks after beginning-of-year benchmark
- ✓ complete data for the beginning-of-year and end-of-year benchmark assessments so that we could compute DCS
- ✓ BOY DORF benchmark scores between 0 and 80 words correct (that is, within 10 points of the BOY goal).



Beginning of Year DORF Words Correct





HLM Procedures: Estimating Slope (OLS and EB)

- OLS and EB Slope of progress was estimated using the HLM 7 software using a random slopes and random intercepts model.
- At the student level, DORF Words Correct (DORFWC) was the outcome variable, and number of weeks after the BOY benchmark (WABOY) was the predictor variable.
- Number of weeks after the BOY benchmark was used to provide a stable and interpretable zero point across multiple disparate school calendars.

$$\begin{aligned} \text{Level-1 Model} \\ \text{DORFWC} &= P_0 + P_1 * (\text{WABOY}) + e \\ \\ \text{Level-2 Model} \\ P_0 &= B_{00} + r_0 \\ P_1 &= B_{10} + r_1 \end{aligned}$$

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HLM Procedures: Estimating Reliability of Pathway

Level of current student performance can be estimated with mean of the last 3 data points or the median of the last 3 data points.

- In previous research, the mean and the median of the final three DORF-WC scores for each student were highly correlated, so it seems reasonable to use them interchangeably.
- Both mean and median were examined with respect to evaluating the stability of progress decisions.
- To enable a direct comparison to slope, level was estimated using the mean computed using HLM 7.01 to fit an intercept only (0 slope) model to the last 3 data points only at week 6.

$$\begin{aligned} \text{Level-1 Model} \\ \text{DORFWC} &= P_0 + e \\ \\ \text{Level-2 Model} \\ P_0 &= B_{00} + r_0 \end{aligned}$$

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Procedures: Rate of Improvement Bands

- Rate of Improvement (ROI) bands were based on a prior analysis of 415,107 third-grade students whose DIBELS Next scores were entered in DIBELSnet and Amplify mCLASS during the 2014-2015 academic year.
- ROI bands were developed using procedures adapted from AIMSweb®, 2012. Students were grouped by their BOY DORF-Words Correct into one of five categories from "very low" (1-10th percentile), to "very high" (91-99th percentile).
- Weekly rate of improvement was calculated for both fall-to-winter (mid-year rate of improvement) and fall-to-spring (year-long rate of improvement). The ROI per week was calculated for each student by dividing the difference in the student's beginning- and middle- or, end-of-year DORF-Words Correct by 18 or 36 weeks, respectively.
- For each category of initial skill the 20th, 40th, 60th, and 80th percentile of rate of improvement was estimated.

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ROI Bands for Zones of Slope

Rate of Improvement (ROI) in DIBELS Oral Reading Fluency-Words Correct (DORF-WC) by Initial Skill (Grade 3)

BOY DORF-WC initial skills	Percentile range	BOY DORF-WC range	Rate of Improvement			
			20th ptile	40th ptile	60th ptile	80th ptile
Very low	1-10	9-39	0.444	0.667	0.944	1.278
Low	11-25	40-58	0.389	0.778	1.167	1.611
Average	26-75	59-105	0.333	0.722	1.111	1.556
High	76-90	106-132	0.000	0.500	0.944	1.500
Very high	91-99	133-186	-0.333	0.222	0.722	1.278

Note. ROI is the weekly DORF-WC growth from BOY to MOY (18 weeks).

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Procedures: Pathways of Progress

Pathways of Progress were based on a prior analysis of 406,266 third-grade students whose DIBELS Next scores were entered in DIBELSnet and Amplify mCLASS during 2014-2015.

1. Students were grouped by BOY DCS for scores between one and the 99.5th percentile rank. For each unique BOY DCS, the 20th, 40th, 60th, and 80th quantiles were calculated for DORF WC.
2. A stiff, spline quantile regression model was fit to each quantile using BOY DCS as the predictor.
3. The predicted quantile scores from the regression model corresponding to each unique BOY DCS were rounded to the nearest one, forming the end-of-year pathway borders.
4. Pathway borders were linearly interpolated for each week after BOY benchmark using the BOY DORF WC at Week 0 and the EOY Pathways of Progress border at Week 18 (the median middle-of-year week).

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Methodology: Procedures/Analysis

- Reliability of each metric was examined using HLM.
- Stability of the decision from week 6 to week 7 for each metric was examined by calculating correlations, percent of exact matches, percent of matches within 1.
- A series of multiple regression models were used to examine proportion of variance in the outcome (EOY DCS) explained by BOY DIBELS Composite Score and each progress metric.
- The additional variance explained by each progress metric beyond initial skill was examined.

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Results: Overview

- Descriptive statistics
- Reliability of individual student decision metrics
- Stability of progress decisions
- Amount of variance accounted for in the full model, and additional variance accounted for by Pathway

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Results: Descriptive Statistics ($n = 1,155$)

Variable	Mean	SD	Min	Max
BOY DORF Words Correct	44.18	17.29	0	80
BOY DCS	129.11	64.73	0	358
EOY DCS	269.20	101.60	6	512
Week 6 OLS Intercept	50.57	17.80	-0.89	100.40
Week 6 OLS Slope	1.46	1.94	-6.11	9.86
Week 6 EB Intercept	50.82	15.87	6.63	93.61
Week 6 EB Slope	1.41	0.57	-0.19	2.96

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Results: Descriptive Statistics ($n = 1,155$)

Variable	Mean	SD	Min	Max
OLS Zone	3.44	1.73	1	5
EB Zone	4.03	1.18	1	5
Median last 3 paths	4.16	1.41	1	5

	Correlation	
Progress Decision	1	2
1. OLS Zone		
2. EB Zone	.24	
3. Median last 3 paths	.61	.28

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Frequency of Pathway or Zone by Type of Metric

Metric	Pathway or Zone									
	1		2		3		4		5	
	Count	Pct.	Count	Pct.	Count	Pct.	Count	Pct.	Count	Pct.
OLS zone	320	28%	71	6%	107	9%	97	8%	560	48%
EB Zone	76	7%	62	5%	147	13%	334	29%	536	46%
Med3 Pth	133	12%	69	6%	65	6%	106	9%	782	68%

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HLM Estimate of Reliability of OLS Slope and Mean of 3 DORF WC

Decision Metric	HLM Estimate of Reliability
6 week OLS slope estimate	.067
6 week EB slope estimate	NA
Mean of final 3 DORF WC in 6 weeks	.914

OLS slope has almost 0 reliability
The final 3 DORF Words Correct has very high reliability.

The reliability of the Empirical Bayes slope was not available using this procedure.

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Week to Week Stability of Progress Decisions

One way to evaluate the stability of decisions about student progress is to compare the decision with 6 weeks of progress monitoring data with the decision with 7 weeks of progress monitoring.

In other words, would we make the same decision next week?

Note that the stability of the decision is not a test-retest reliability coefficient because both decisions share data:

- Slope decisions at 6 weeks and 7 weeks will share 6 weeks worth of data.
- Pathways decisions based on the most current 3 assessments at 6 weeks and 7 weeks will share 2 of 3 data points.

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6 Week and 7 Week Decision Stability

Metric	Stability correlation coefficient	Percent of exact agreement	Percent of agreement within 1
OLS zone	.72	61%	79%
EB Zone	.92	66%	100%
Med 3 Pathways	.78	77%	88%

Empirical Bayes has strong stability from week to week.

Median of 3 Pathways had the strongest exact agreement.

Even though OLS slope has almost 0 reliability, the stability of decisions based on OLS zone of progress is not out of the ballpark.

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Additional Variance Explained in End-of-Year DIBELS Composite Score

Progress Decision	R ²	Percent additional variance explained	t
OLS zone	.5881	1.9%	7.25*
EB Zone	.6427	7.3%	15.38*
Median of 3 Pathways	.5971	2.8%	8.92*

All three progress decisions contributed significantly to end-of-year outcomes over and above the beginning-of-year score. Empirical Bayes was the strongest.

Base Model: EOY Composite = 137.72 + 1.15 * com3b +
-0.00398 * (com3b - 129.11)²

Base model R² = .5693

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Summary of Results

1. Consistent with previous research, OLS slope had extremely low reliability. Nevertheless, OLS slope displayed week-to-week stability and predicted end-of-year outcomes.
2. Empirical Bayes Slope based on the reliable part of the OLS slope displayed strong week-to-week stability and provided the strongest prediction of end-of-year outcomes.
3. Median of 3 Pathways of Progress based on a very reliable metric displayed strong week-to-week stability as exact matches and predicted end-of-year outcomes.

Next we looked more closely at individual student decisions and observed some perplexing patterns.

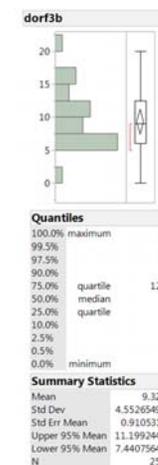
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Perplexing Pattern: OLS Slope with Adequate Progress, EB Slope with Low Progress

66 Students had OLS ROI Zone of 4 or 5, and had EB ROI Zone of 1 or 2.

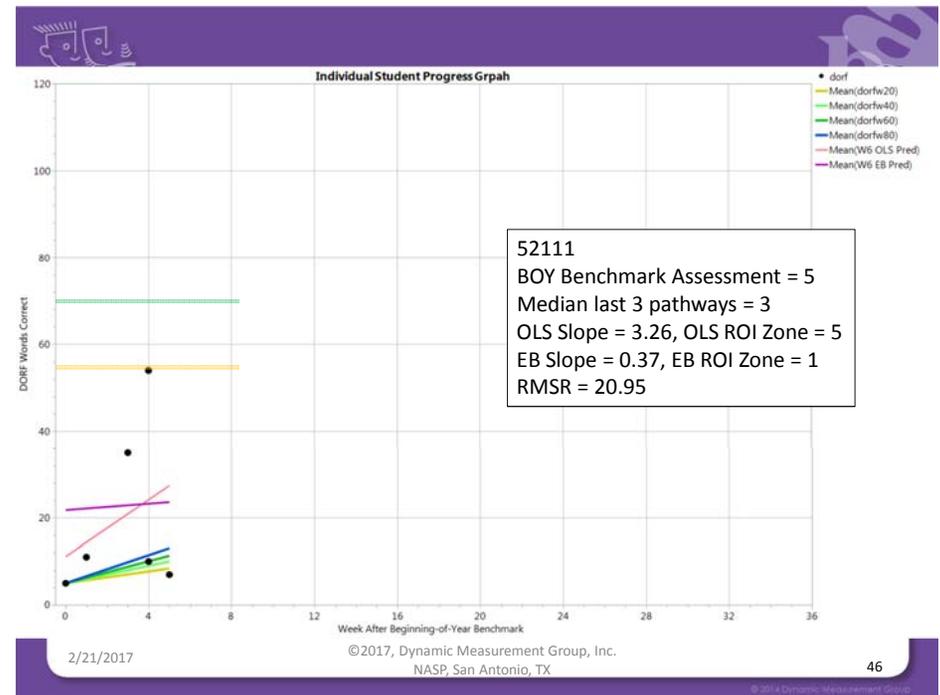
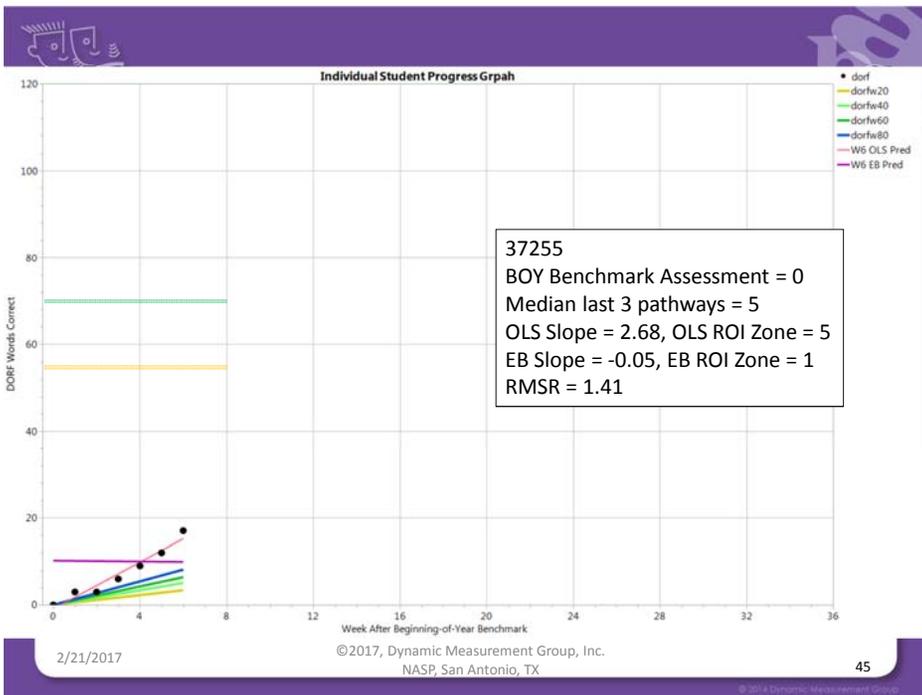
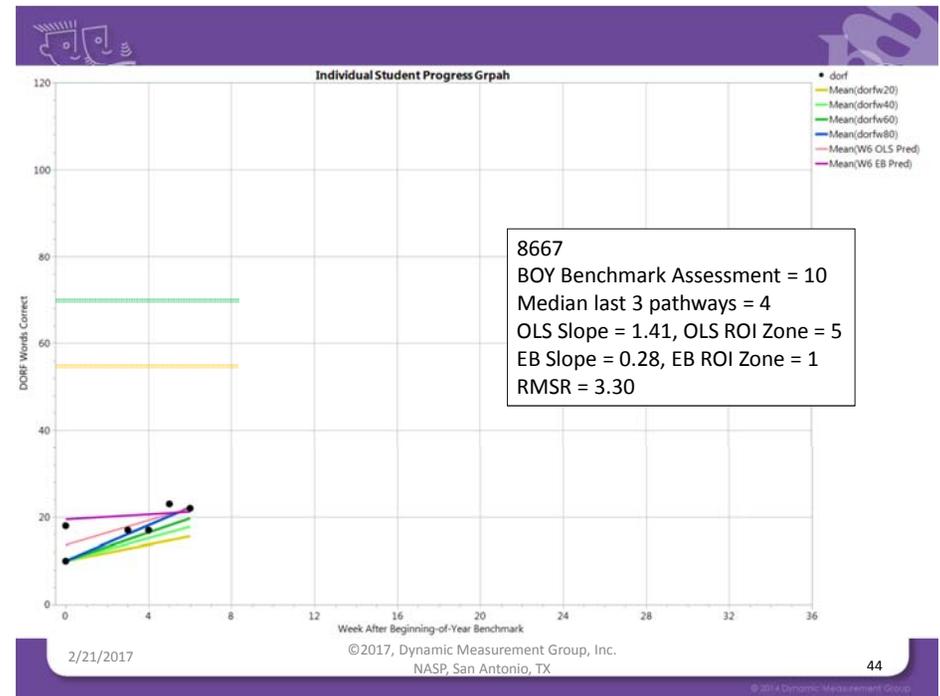
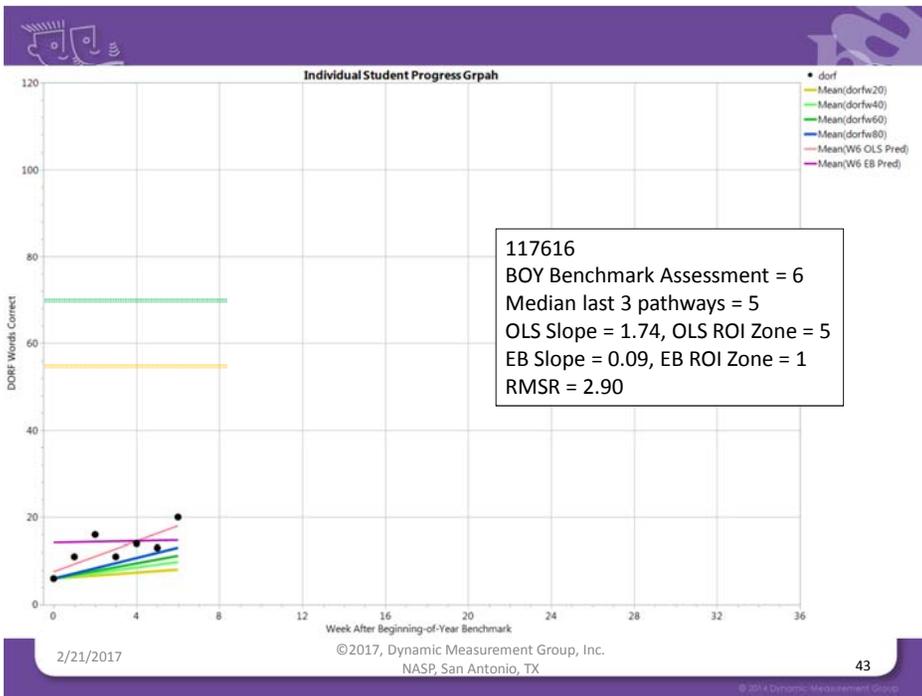
- 25 Students had
 - OLS ROI Zone of 5, **well above typical progress**, and had
 - EB ROI Zone of 1, **well below typical progress**.
 - All 25 students had BOY Benchmark DORF Words Correct less than or equal to 20.

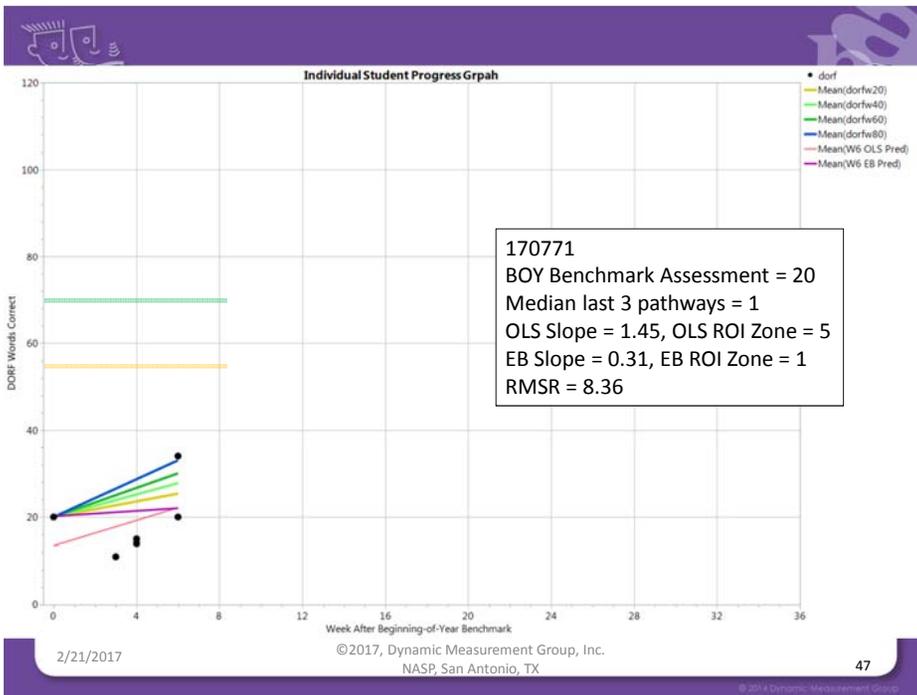


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Perplexing Pattern: OLS Slope with Low Progress, EB Slope with Adequate Progress

263 Students had OLS ROI Zone of 1 or 2, and had EB ROI Zone of 4 or 5.

- 81 Students had
 - OLS ROI Zone of 1, **Well below typical progress**, and had
 - EB ROI Zone of 5, **Well above typical progress**.
 - All had BOY Benchmark DORF Words Correct greater than 30, with most greater than 50.

Distributions

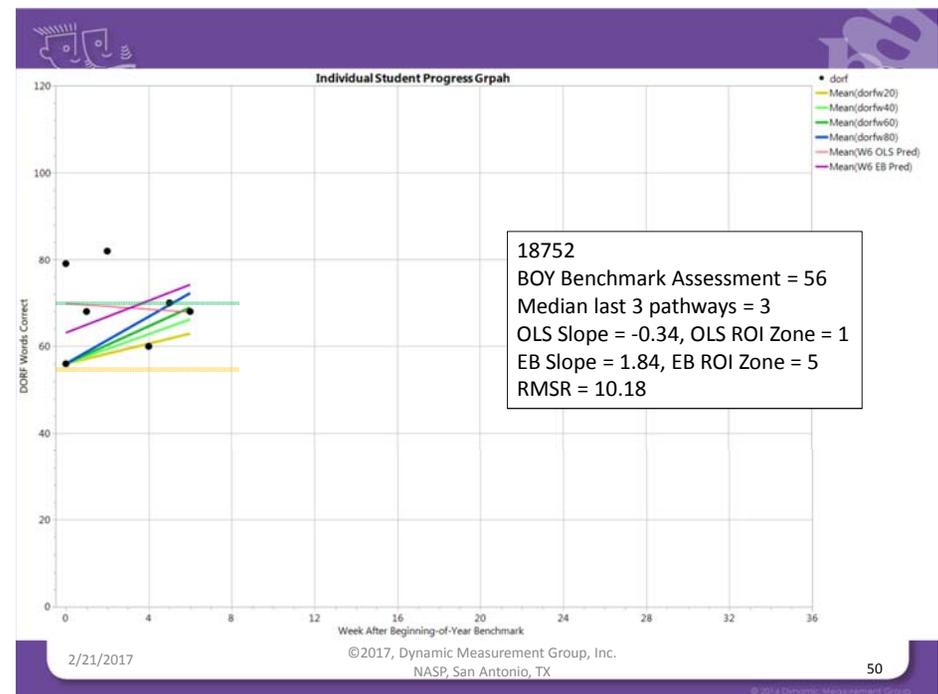
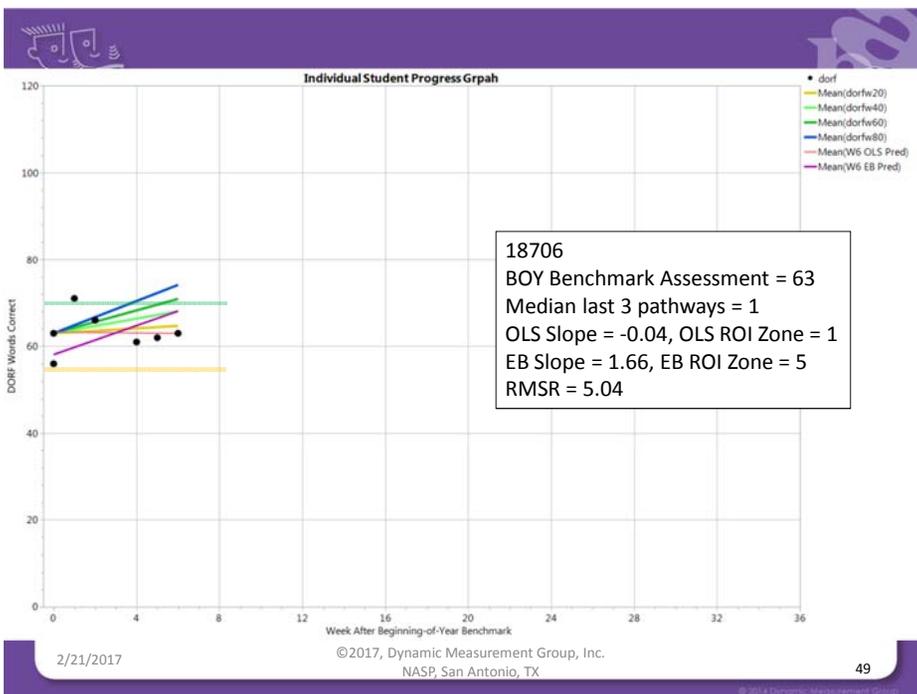
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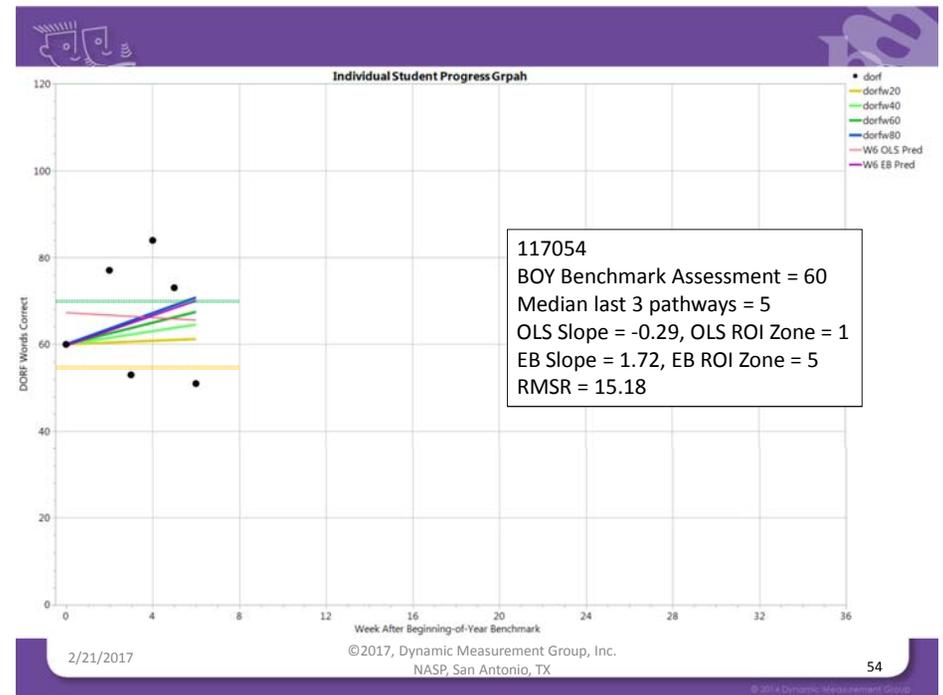
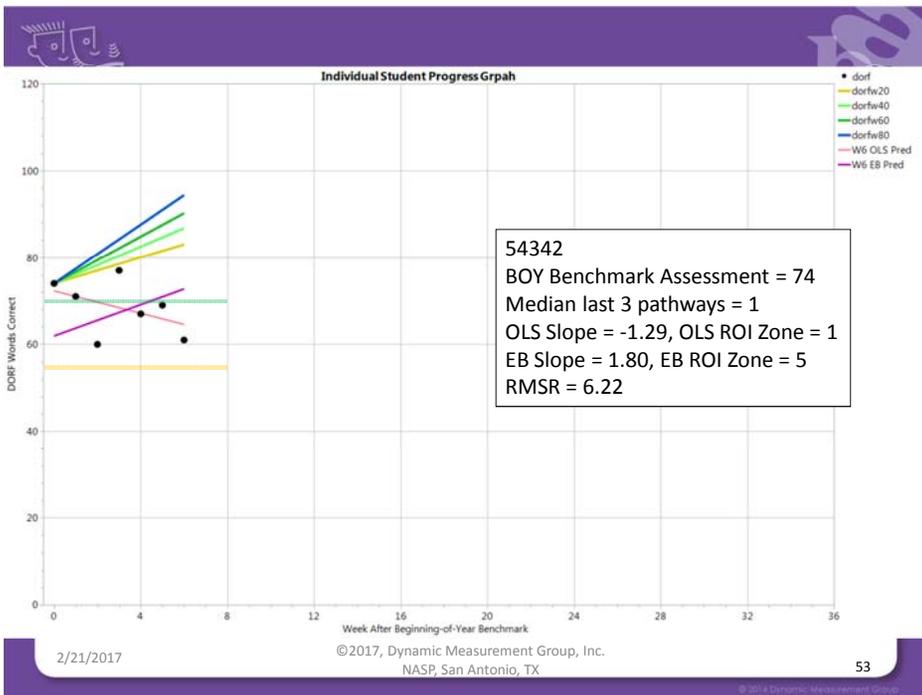
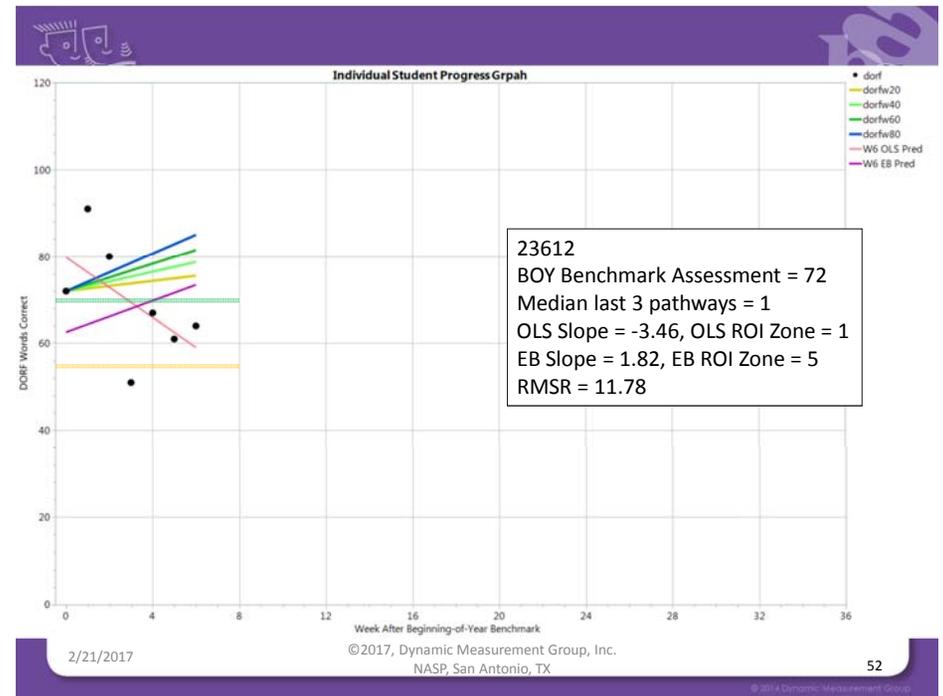
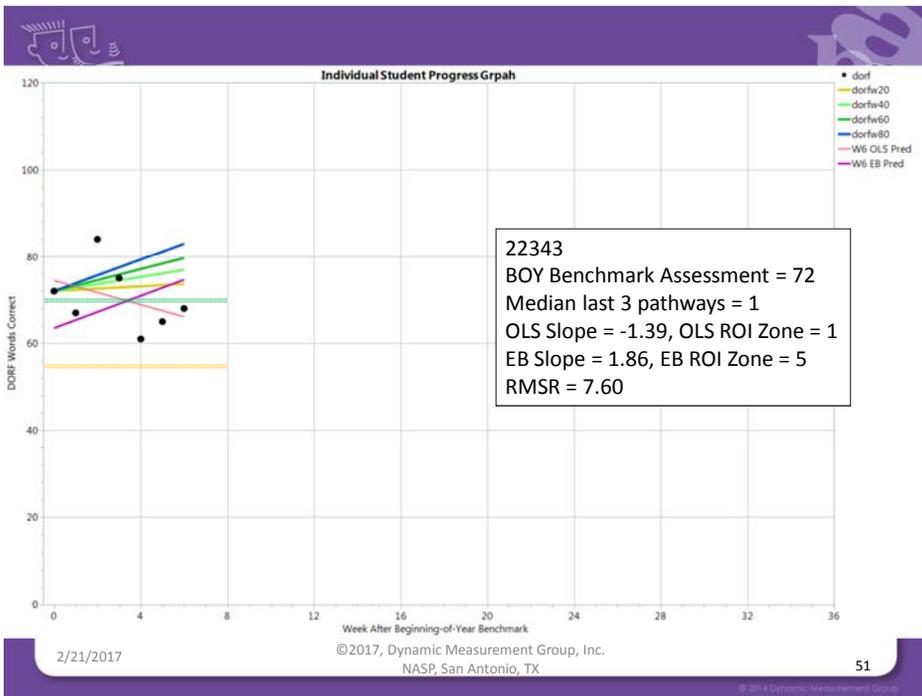
100.0%	maximum	79
99.5%		79
97.5%		79
90.0%		75.6
75.0%	quartile	70.5
50.0%	median	64
25.0%	quartile	59
10.0%		50
2.5%		36.05
0.5%		32
0.0%	minimum	32

Summary Statistics

Mean	62.901235
Std Dev	10.470918
Std Err Mean	1.163453
Upper 95% Mean	65.216545
Lower 95% Mean	60.585924
N	81

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HLM Empirical Bayes Slope Hypothesis

The HLM Empirical Bayes Slope is a true multivariate empirical Bayes that uses all of the information in the mean Beta vector for unreliable information. Thus, the HLM EB slope is very little OLS slope (reliability = .07) and almost completely the overall level of performance.

OLS intercept explains 87.67% of the variance in HLM EB slope.

Mean of all DORF Words Correct in the 6 weeks correlates .966 with HLM EB slope.

So, HLM EB slope appears to be telling us more about the student's overall level of reading skills than about the student's rate of change.



Correlations of Student Progress Decision Metrics with Level of Reading Skill

Progress Decision Metric	BOY DORF WC	6 Week Mean DORF WC
OLS slope zone	.03	.26
EB slope Zone	.80	.90
Median of 3 pathways	.02	.26



Limitations

- These data represent the way DIBELS Next is used in practice.
- Things we do not know:
 - Assessment fidelity
 - Assessor training
 - Level of instructional support
 - Changes in levels of support



Conclusions

1. The HLM Empirical Bayes slope estimates displayed perplexing patterns and appeared to represent level of student skills rather than rate of student progress.
2. The OLS slope estimate again displayed distressingly low reliability at 6 weeks, and yet decisions about progress based on OLS slope displayed week-to-week stability and predicted end-of-year outcomes.
3. Pathways of Progress provided strong week-to-week stability and predicted end-of-year outcomes.



Unanswered Questions

If OLS slope has almost no reliability, how can it display week-to-week stability and predict outcomes?

Is Empirical Bayes strong stability and prediction of end-of-year outcomes because it is a measure of student skill level rather than a measure of student progress?

“We have not succeeded in answering all our problems. The answers we have found only serve to raise a whole set of new questions. In some ways we feel we are as confused as ever, but we believe we are confused on a higher level and about more important things.”

— [Earl C. Kelley](#)



Implications For Practice

- Know Where Students Start
 - A student who begins the year at the cut-point and does not make progress is unlikely to achieve subsequent grade level outcomes without additional support.
- Set Ambitious Goals
 - Use the DIBELSnet goal setting utility to determine and select goals that reflect Typical, Above Typical, or Well Above Typical progress.
- Monitor/Evaluate Student Progress
 - Examining the data on their progress monitoring graph, including the Pathway.
 - Examine middle- and end-of-year classroom Pathways Reports



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