Title: Examination of Latent Classes and Growth Trajectories in Reading Comprehension and Fluency CBMs for Grades 3-5.

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Background / Context:

Response to Intervention

Response to intervention (RTI) is a promising framework for identifying students at risk for reading difficulties (Fletcher, Coulter, Reschly, & Vaughn, 2004; L. Fuchs, Fuchs, & Speece, 2002; Vaughn & Fuchs, 2003). Within an RTI framework, instruction is typically organized into three tiers, representing different levels of need and subsequent intensity of intervention. In Tier 1, students receive general education instruction in a group setting. Placement into the two more intensive tiers (Tier 2 and 3) is generally the result of poor performance on either a screening assessment or poor initial performance on a screening assessment followed by failure to show adequate progress on subsequent progress monitoring measures. Students who are identified as at-risk for academic failure during the screening process are identified for Tier 2 instruction, where they are provided with targeted, group-based, intensive instruction that is matched to their needs and level of achievement. The screening mechanism consists of administrating one-time point measures in fall, winter, and spring during the academic year. Students who do not respond to Tier 2 interventions (i.e., non-responders) are placed into Tier 3, where they are provided with more intensive individualized instructional interventions that aim to remediate students' deficits, and their progress with acquiring critical skills is monitored closely and with greater frequency.

Differences in Reading Development between early and later Elementary Grade Students

In early elementary grades, students focus on *learning to read* by building on foundational components of speech and print – phonemes, phonological units, letter sounds – and the systematic relations between these components (Chall, 1993). In later elementary grades, students transition to *reading to learn*, where they are challenged by increased reading demands and are expected to understand text in greater depth (Chall, 1996). In the later grades, reading comprehension, word reading, and fluency are identified as increasingly important (Speece et al., 2010), as opposed to phonological awareness, phonics, decoding, word recognition, word reading fluency, and spelling, which are important predictors of student reading performance in the early grades (National Institute for Child Health and Human Development [NICHD], 2000). The increased reading demands and the diminishing role of oral reading fluency may contribute to the current unsatisfactory accuracy rate in identifying students at risk for reading difficulties in later elementary grades. Furthermore, as Speece (2005) pointed out, "children continue to develop on the very skills we use as screens, but our methods rarely take this development into account".

Identification of Students at-risk for Reading Difficulties

Current methods of identifying and intervening with students in the early elementary grades with reading difficulties have been relatively successful (Compton et al., 2006; Jenkins, 2003; Speece & Case, 2001). However, many concerns remain regarding the valid identification of students with reading difficulties in later elementary grades (Jenkins, Hudson, & Johnson, 2007). Of particular concern is the appropriateness of the use of Oral Reading Fluency (ORF) measures, commonly used in the early elementary grades, to identify older students (Jenkins, Hudson, & Johnson, 2007; Yovanoff, Duesbery, Alonzo, & Tindal, 2005). It may not be reasonable to assume that ORF would be equally effective for identifying students in the upper elementary grades with reading difficulties.

Alternative Method of Identifying Students at Risk for Reading Difficulties

Growth modeling techniques, such as growth mixture modeling (GMM) and latent class growth analysis (LCGA) that can identify subgroups of students with different developmental profiles, can be a viable alternative classification method for identifying students at risk for reading difficulties (Boscardin, Muthén, Francis, & Baker, 2008). These methods have been used to identify students at risk for reading difficulties with distinct developmental trajectories from a larger heterogeneous population (Boscardin, Muthén, Francis & Baker, 2008 & Muthén, Khoo, Francis, & Boscardin, 2002). Conventional growth models such as random coefficient model (Raudenbush & Byrk, 2002) and latent growth curve model (Meredith & Tisak, 1990) have been widely used to examine growth. These methods assume that individuals originate from a single population with one growth trajectory. However, this assumption may not be reasonable because it ignores naturally-occurring individual differences. The average growth trajectory assumption also does not apply to the RTI framework, where students are grouped into different tiers of instruction. Therefore, growth modeling approaches such as GMM and LCGA that assume that heterogeneity of growth trajectories exists within the larger population could be more suitable for capturing information about latent classes and their growth profiles.

A few researchers have studied the heterogeneity of reading growth trajectories. In a study examining first-grade word recognition development predicted by kindergarten phonemic awareness, Muthén et al. (2002) found four distinct groups of students. Later, Boscardin et al. (2008) found 10 different developmental patterns among students in grades K-2 from a 3-year longitudinal study, identifying one class of students with a distinct developmental pattern who were most at risk for reading difficulties. Despite the emerging trend of using GMM in reading research, most researchers have focused on the development of students in only the early elementary grades. In this study, we extend the current literature on curriculum-based measurement (CBM) formative assessments from early to the later elementary grades by exploring the growth patterns of multiple latent classes using reading comprehension and fluency CBM measures. These topics will be examined using LCGA, a special type of GMM that makes the assumption that there are different growth trajectories for each unobservable class and that all individual growth trajectories within a class are homogeneous.

Purpose / Objective / Research Question / Focus of Study:

This study extends the current literature on curriculum-based measurement (CBM) formative assessments in reading for a later elementary grade by examining differences in the latent classes and reading growth patterns of students in grades three through five using a popular assessment system (easyCBM) reading comprehension and reading fluency measures. These topics will be examined using latent class growth analysis (LCGA), a special type of GMM that makes the assumption that there are different growth trajectories for each unobservable class and that all individual growth trajectories within a class are homogeneous. LCGA was selected as the preferred growth model for this study because it takes into account the heterogeneity of growth and thus might provide reliable predictions for later development.

Setting:

Data for this study come from a large data set gathered in the 2009-10 school year at seven school districts in the Pacific Northwest. For this study, data from one district was selected for analysis to control for differences in RTI programs.

Population / Participants / Subjects:

Three cohorts of students in grades three through five will be examined. Data include student characteristics like gender (47-50% male, 50-53% female), disability status (15-17% SPED), language proficiency status, (16-17% ELL) and ethnicity (2-3% Black, 71-73% White, and 9-11% Hispanic) across grades 3-5 (see Table 1).

Intervention / Program / Practice:

Data from students' performance on the district-mandated benchmark screening assessments administered in fall, winter, and spring were included in this study. For all three grades included in this study, these measures included the fall, winter, and spring forms of grade-level tests of Passage Reading Fluency (PRF) and Reading Comprehension (MCRC) (see descriptive in Table 2). These tests were administered by district personnel as part of their universal screening practice, three times per year. The PRF measures were administered individually, with a test administrator scoring students for accuracy and rate as they read aloud for one minute from grade-level narrative fiction passages. The MCRC measures were group-administered in a computer lab setting, where student responses were captured and scored automatically by the computer as students completed the online assessments.

Research Design:

This study involves analysis of extant data collected by the school district and shared with the authors for analysis.

Data Collection and Analysis:

Piecewise latent class growth analysis (LCGA) was used to model growth of the three cohorts who took the easyCBM MCRC and PRF measures in 2009-10. Piecewise growth modeling was used because non-linearity of growth patterns was observed in the data. LCGA assumes that there is heterogeneity in growth patterns and allows different classes of individuals to vary around different mean growth curves. LCGA also assumes that there is zero within-class variance on the intercept and slope (i.e., individuals in each class are homogenous).

Model selection and model fit were evaluated using the Akaike Information Criteria (AIC), Bayesian Information Criteria (BIC), Adjusted BIC (ABIC), Lo-Mendell-Rubin Likelihood ratio test (LMR), and the Adjusted LMR likelihood ratio test. Lower AIC, BIC, and ABIC values suggest better model fit. The LMR and Adjusted LRM likelihood ratio tests compare the k class model to a k-1 class model (Nylund, Asparaouhov & Muthén, 2007), with significant values indicating better fit. Entropy values were used to judge the precision of the classifications, with entropy values approaching 1 as evidence of good classification (Muthén, 2004). In addition to these criteria, other decisive factors were also taken into consideration to determine the optimal number of latent classes, including: (a) the overall interpretability of the model based on proportion of students in each class, (b) the estimated posterior probabilities and most likely latent class membership, and (c) the visual plots of latent classes of estimated means and observed individual trajectories.

Findings/Results for Grade 4 Cohort:

Findings for all three grades will be shared at the conference. Here, we present findings for a single grade (grade 4) in the interest of brevity.

LCGA Models Using Grade 4 MCRC Measures

A 4-class solution from an unconditional piecewise LCGA model was identified as the best solution based on the criteria described earlier (see Figure 1 below). Class 3 (n=162, 38%) was the highest performing group, but showed a slight decrease in performance from fall to winter (η_1=-.57, $p < .05$) and minimal growth from winter to spring (η_2=.50, $p < .05$). Class 2 (n=333, 29%) was the second lowest group and showed a trajectory of above the 20th percentile. Class 2 displayed the steepest growth from fall to winter in this 4-class unconditional piecewise LCGA model (η_1= 3.42, $p < .05$), but almost no growth from winter to spring (η_2=.05, $p < .05$). Class 4 (n=444, 38%), the majority of students, started at slightly below the 50th percentile and displayed small growth overall across the school year (η_1=.88, $p < .05$; η_2 =-.17, $p > .05$). Class 1 (n=219, 19%) was the lowest performing group, with their trajectory slightly above the 10th

percentile throughout the year. Class 1 displayed steeper growth from fall to winter (η_1= 2.32, p < .05) and less growth from winter to spring (η_2=-.36, p > .05).

LCGA Models using Grade 4 PRF Measures

A 7-class solution was the best solution for the unconditional piecewise LCGA results modeling growth in PRF (see Figure 2). All classes demonstrated significant positive growth from the fall to winter. Classes 4, 6, and 7 displayed the steepest growth, ranging from 22-25 words correct per minute (WCPM) while other classes (the top two performing classes and the two lowest performing classes) displayed smaller positive growth (15-18 WCPM). Much smaller growth rates in WCPM were observed from winter to spring, however, particularly for the bottom four classes (Classes 6, 7, 5, and 2); growth rates of 2-8 WCPM were observed in the bottom four classes compared to growth rates of 13–17 WCPM for the top three classes. Class 2 had trajectories lower than the 10^{th} percentile, and classes 5 and 7 had trajectories between the 10^{th} and 50^{th} percentile.

Conclusions:

Results from this study provide preliminary insights into development in reading comprehension and reading fluency as students progress from grades three through five. Given that NCLB requires districts to show that students have grown appropriately toward meeting the state standards, results from LCGA models using benchmarking data can shed light on concerns related to the expected learning trajectories of multiple student groups, with special interest students with exceptionally low scores and/or growth that are most likely the ones who need special attention in the classroom. Teachers can be better prepared by having more information to create strategic homogenous instructional groups by targeting students' weaknesses. Greater understanding of the lowest performing group also can help district and school administrators make informed decisions to allocating adequate resources and plan for appropriate district-wide RTI programs.

Appendices

Appendix A. References

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Appendix B. Tables and Figures

Table 1. Demographic information.

		Grade 3		Grade 4		Grade 5	
		n	%	*n*	%	*n*	%
Gender	Male	692	52.8	586	50.2	701	51.7
	Female	619	47.2	581	49.8	656	48.3
Ethnicity	American Indian/Alaskan Native	22	1.7	23	2.0	24	1.8
	Asian/Pacific Islander	58	4.4	40	3.4	69	5.1
	Black	32	2.4	33	2.8	35	2.6
	Hispanic	129	9.8	139	11.9	135	9.9
	White	957	73.0	833	71.4	963	71.0
	Multi-Ethnic	40	3.1	56	4.8	52	3.8
	Decline/Missing	24	1.8	16	1.4	35	2.6
	Missing	49	3.7	27	2.3	44	3.2
ELL	Yes	58	4.4	45	3.9	48	3.5
	No	1253	95.6	1122	96.1	1309	96.5
SPED	Yes	209	15.9	198	17.0	236	17.4
	No	1102	84.1	969	83.0	1121	82.6

Table 2. Descriptive statistics.

Grade	Measure Scores	*n*	Min	Max	*M*	*SD*
3	Fall09MCRC	1234	0	219	91.71	40.84
	Wint10MCRC	1245	0	308	123.29	45.71
	Spr10MCRC	1233	3	255	122.91	43.74
	Fall09PRF	1224	0	19	11.16	3.75
	Wint10PRF	1236	0	18	10.97	3.00
	Spr10PRF	1254	0	20	14.30	3.85
4	Fall09MCRC	1109	0	20	12.64	4.29
	Wint10MCRC	1118	2	20	14.36	3.43
	Spr10MCRC	1129	1	20	14.26	3.58
	Fall09PRF	1113	6	263	115.41	37.99
	Wint10PRF	1126	5	269	136.18	37.58
	Spr10PRF	1138	9	340	145.32	42.60
5	Fall09MCRC	1234	0	219	91.71	40.84
	Wint10MCRC	1245	0	308	123.29	45.71
	Spr10MCRC	1233	3	255	122.91	43.74
	Fall09PRF	1224	0	19	11.16	3.75
	Wint10PRF	1236	0	18	10.97	3.00
	Spr10PRF	1254	0	20	14.30	3.85

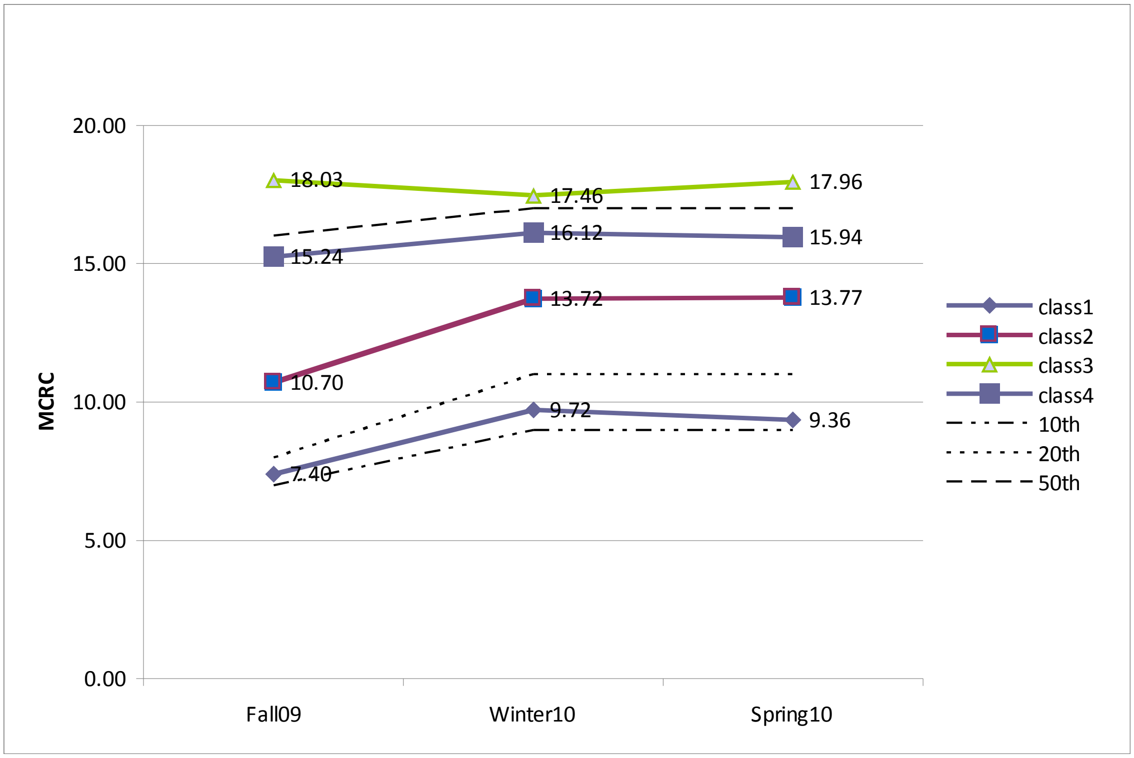

Figure 1. Piecewise LCGA model based on MCRC measures.

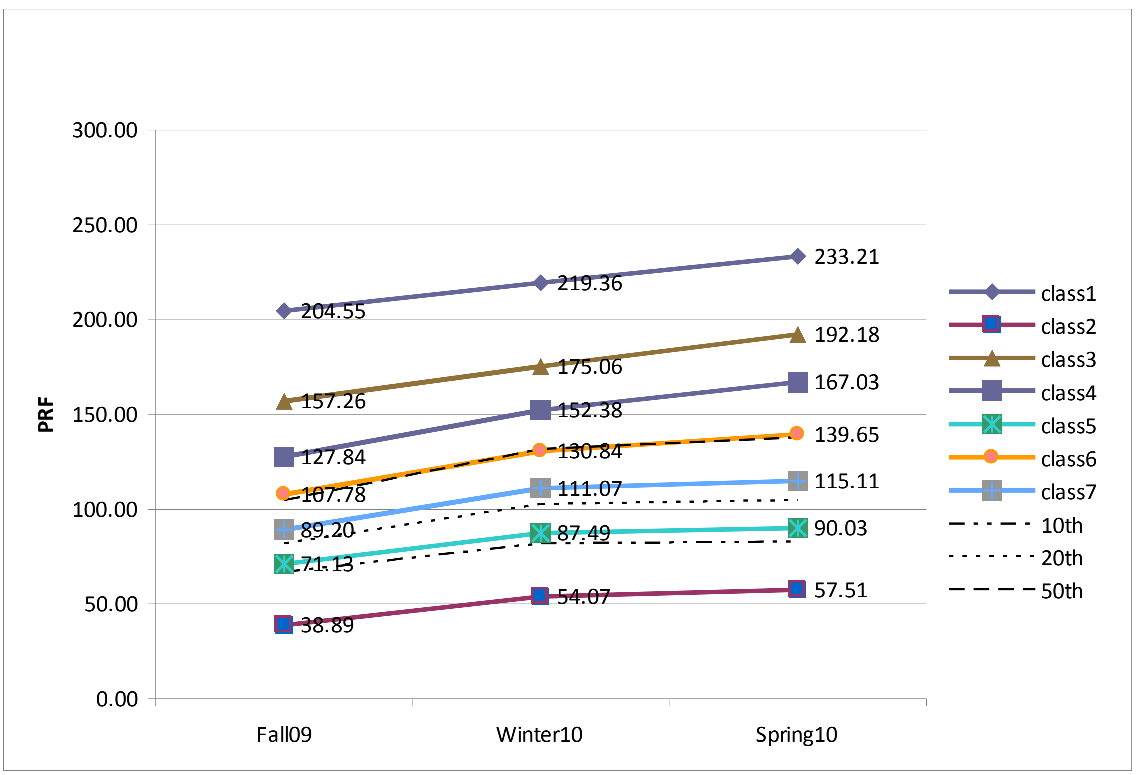

Figure 2. Piecewise LCGA model based on PRF measures.