Evaluating Elementary Students' Response to Intervention in Written Expression

Sterett Mercer, Ioanna Tsiriotakis, Eun Young Kwon,
Joanna Cannon
University of British Columbia

The Problem

Research tells us that some academic interventions and intervention approaches work better than others (on average)…

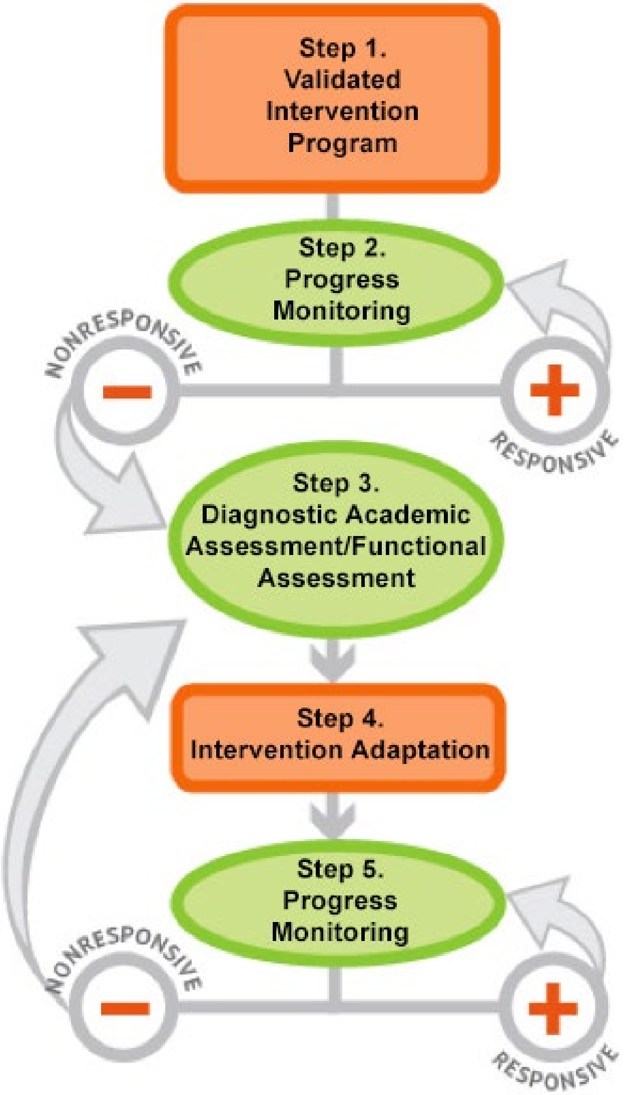
But how do we know if an intervention is working for a particular student?

[and what do we do when it isn't working?]

Purpose

- Introduce Data-Based Individualization (DBI) for service delivery
- Introduce Curriculum-Based Measurement (CBM) as a data source
- Discuss challenges & solutions for CBM of written expression

What is Data-Based Individualization (DBI)?



- A decision-making framework for providing intensive academic intervention
    - Assumes good interventions don't work for all students
- It generates evidence that either:
    - The intervention is working as designed
    - Your <u>experimental teaching</u> is working

National Center on Intensive Intervention, https://intensiveintervention.org/

Data-Based Individualization Requires Data

- Curriculum-based measurement (CBM) data are often used for this purpose
  - Indicators of overall progress in an academic skill area
  - Standardized
  - Efficient (easy to administer and score) and repeatable
  - Documented standards for performance
    - Criterion- and/or norm-referenced
  - Evidence of reliability and validity for screening and progress monitoring
    - Alternate-form reliability
    - Predicts performance on more comprehensive assessments of the skill

CBM Example: Oral Passage Reading

- Also called ‘oral reading fluency’
  - Read one or more field-tested passages for 1 min
  - Record the number of words read correctly
- Scores predict performance on comprehensive assessments of broad reading skill (Reschly et al., 2009)
  - Can identify students at-risk of difficulty/disability
  - Sensitive to improvements in general reading skill
- Easy to administer and use for decision making
  - Compare to norms
  - Graph data from repeated administrations and visually analyze progress

CBM in Written Expression (CBM-WE)

- The original idea (~1980s)
  - Present one narrative prompt (story starter: One day at school…)
  - 1 min to plan and 3 min to write
  - Score with simple metrics like word count
- This (and similar procedures) work pretty well in lower elementary grades for screening and monitoring, less so as student writing becomes more complex (McMaster & Espin, 2007)
  - Key issues: reliability, validity (including face validity), and feasibility

CBM-WE: Reliability

- Big Idea: Typical procedures do not yield reliable data for screening or progress monitoring

- Collected three 7 min narrative writing samples collected in fall, winter, and spring (*n* = 145 grade 2-5 students in Houston, TX, area)
  - Generalizability theory analyses to determine optimum sample duration and number of samples needed
  - Reliability < .80 for absolute screening decisions based on one 7 min sample
  - Reliability < .80 for decisions about student growth even with three 7 min writing samples

Keller-Margulis, Mercer, & Thomas (2016)

CBM-WE: Validity

- Big Idea: More complex scoring methods (than total words) improve validity, but greatly reduce feasibility

- Metrics like correct word sequences (CWS) have higher validity coefficients
  - Counts of the number of adjacent words that are spelled correctly and make sense in context
    - Considers aspects spelling, punctuation, syntax, and semantics
  - Better indicator of writing quality, but more time consuming and harder to reliably score
    - Feasibility concerns compound with multiple, longer duration writing samples

Potential Solution: Automated Text Evaluation

- Use computer software that considers and quantifies many characteristics of words, sentences, and discourse to evaluate CBM-WE writing samples
  - Commercial applications are already available, Project Essay Grade (Wilson, 2018)
    - It works well, but no info on how samples are scored and $$$
  - Develop open-source alternatives (Mercer et al., 2019)
    - Need to develop scoring models
    - Others can build on this work
    - Could be incorporated in data-management software

Current Project

- Can automated text evaluation be used to predict writing quality for longer duration narrative samples from students with substantial learning difficulties?
  - Convergent and discriminant validity (writing vs. reading and math)
- Are the scores sensitive to student skill growth from fall to spring?

Context and Sample

- Students participating in 1:1 academic intervention beyond school hours at the Learning Disability Society of Greater Vancouver (http://ldsociety.ca/)
- For training computer models:
  - 10 min picture-prompted narrative samples (*n* = 204) collected in Sep/Oct and May/June each year for program planning and evaluation from 105 students
- For evaluating validity:
  - Non-random sample of 33 students (grades 3-9) with standardized assessment scores in writing, reading, and math

Measures: Holistic Writing Quality

- Used to train automated text evaluation models for Sep/Oct and May/June picture-prompted samples
- Paired comparison method (Thurstone, 1927)
  - Each rater identified best sample for 3000 pairs of samples
  - Aggregated to a continuous quality score using ranking algorithms
    - High inter-rater reliability (r = .95)
- Raters were asked to consider substantive quality (ideation, word choice, text structure)
  - Tiebreaker: Which sample would you most like to read more of?

Measures: Automated Writing Quality

- Each picture-prompted writing sample submitted to ReaderBench (Dascalu, Dessus, Trausan-Matu, Bianco, & Nardy, 2013)
  - Open-source software intended to assess text characteristics predicting reading comprehension difficulty
    - Provides ~200 indicators of word complexity, lexical diversity, syntactic complexity, cohesion, etc.

- Machine learning algorithms used to predict holistic quality ratings with RB scores as inputs
  - Partial least squares (PLS) regression worked best
  - 85% of variance in quality ratings explained
  - Algorithm-predicted quality used in validity analyses

Measures: Validity Assessments (May/June)

- Standardized Written Expression
  - Test of Written Language (4th ed.) constructed response (story writing)
    - Picture prompted, 5 min to plan, 15 min to write
    - Contextual Conventions (CC): spelling and grammar
    - Story Composition (SC): vocabulary, plot, interest to reader
- Standardized Broad Reading and Broad Math
  - aReading and aMath computerized adaptive tests
  - ~20 min to administer, assesses skills from K – Grade 12
  - https://charts.intensiveintervention.org/chart/academic-screening

Results: Convergent and Discriminant Validity

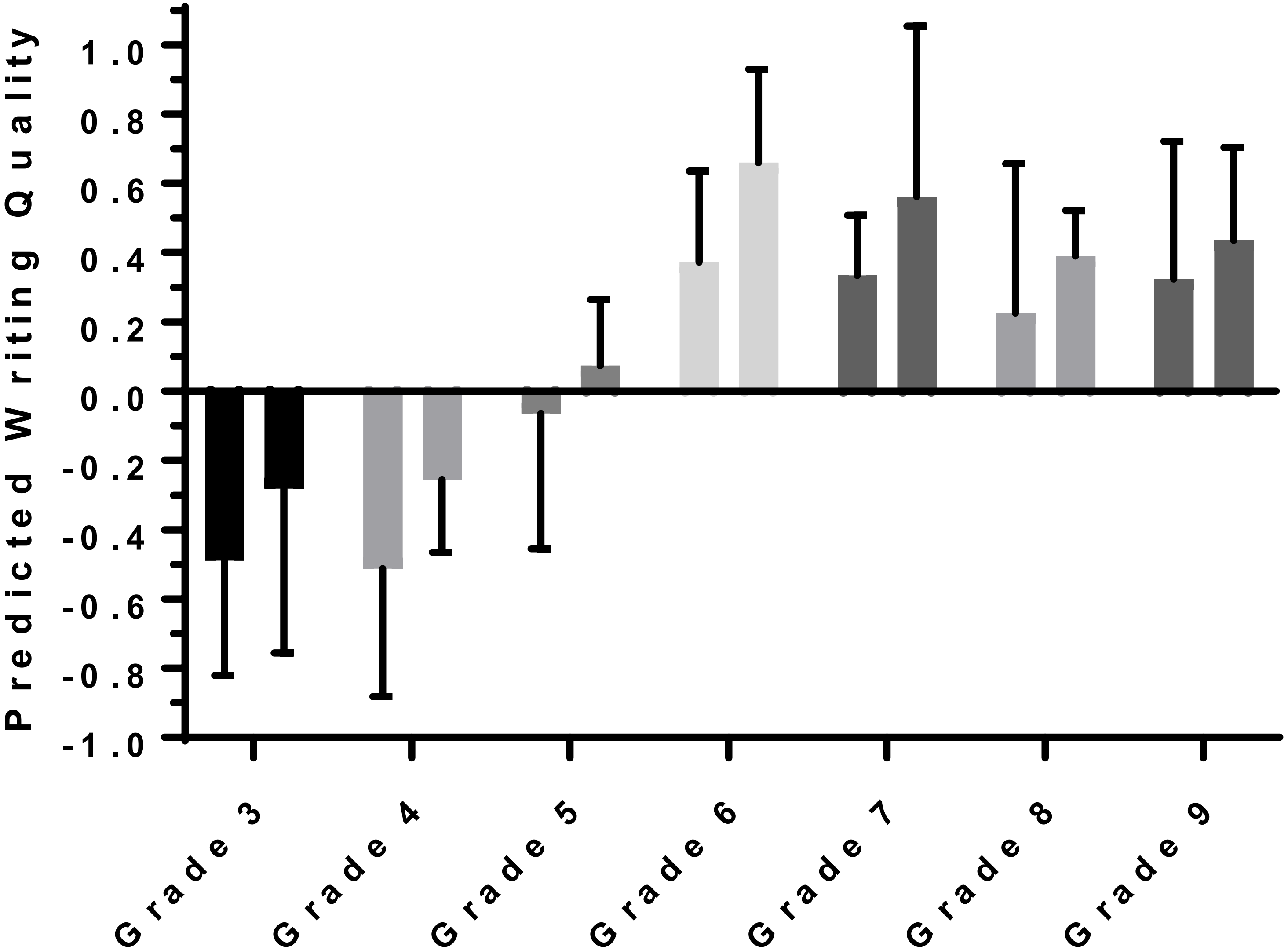
Table 1. *Automated quality scores in relation to standardized writing, reading, and math scores*

	TOWL CC	TOWL SC	aReading	aMath
	r (R^2)	*r* (R^2)	*r* (R^2)	*r* (R^2)
Fall Quality	.69 (.48)	.47 (.22)	.53 (.28)	*.24 (.06)*
Spring Quality	.76 (.57)	.53 (.28)	.56 (.31)	*.35 (.12)*
TOWL Quality	.78 (.60)	.69 (.48)	--	--

Note. n = 33. TOWL = Test of Written Language (4th ed.), CC = Contextual Conventions, SC = Story Composition. Values in italics are not statistically significant (a = .05).

<u>Incremental validity compared to typical CBM-WE scoring</u>
TWW: r = .47 and .59 with fall and spring TOWL CC; CWS: r = .67 and .67

Results: Sensitivity to Growth



- Statistically significant ($p < .001$), moderate-to-large overall change ($d = .77$) from fall to spring on automated quality scores

Discussion: Key Findings

- Good evidence of convergent and discriminant validity for use of automated text evaluation with agency-designed writing sample process to predict performance on more comprehensive assessments of academic skill
  - For students with significant learning difficulties participating in intensive intervention beyond school hours
  - Replicates and extends similar findings with a U.S. general education sample
  - Generalizability of automated scoring algorithm when applied to TOWL writing sample
- Automated quality scores showed evidence of student writing skill growth across a wide range of skill/grade levels (3-9)
- (Very) preliminary evidence that this could work for screening and progress monitoring in a DBI/CBM framework

Defensible Decisions Require Good Data

- Potentially very substantial improvements in scoring feasibility for screening and monitoring large numbers of students
  - Plus fewer concerns with inter-scorer agreement
- Can be used to generate local standards for performance (norms and criteria)
  - For identifying student needs, monitoring outcomes, evaluating programs, and allocating resources
- <u>Not intended to replace evaluation of writing by teachers</u>
  - Can assist teachers in evaluating and tracking overall quality, while freeing up time to provide detailed, formative feedback on areas to improve (Wilson & Czik, 2016)

Closing

- Acknowledgements
  - Funding
    - Social Sciences and Humanities Research Council of Canada
    - U.S. Department of Education, Institute of Education Sciences
      - The opinions expressed are those of the authors and do not represent the views of the Institute or the U.S. Department of Education.
    - Chris Spencer Foundation
  - Special Thanks
    - Staff and Students of the Learning Disabilities Society of Greater Vancouver

- More Information
  - Slides and paper: https://ecps.educ.ubc.ca/person/sterett-mercer/

References

- Dascalu, M., Dessus, P., Trausan-Matu, Ş., Bianco, M., & Nardy, A. (2013). ReaderBench, an environment for analyzing text complexity and reading strategies. In H. C. Lane, K. Yacef, J. Mostow, & P. Pavlik (Eds.), *Artificial Intelligence in Education: 16th International Conference Proceedings* (pp. 379-388). Berlin, DE: Springer.
- Keller-Margulis, M. A., Mercer, S. H., & Thomas, E. L. (2016). Generalizability theory reliability of written expression curriculum-based measurement in universal screening. *School Psychology Quarterly, 31*, 383-392.
- McMaster, K. L., & Espin, C. A. (2007). Technical features of curriculum-based measurement in writing. *The Journal of Special Education, 41*, 68-84.
- Mercer, S. H., Keller-Margulis, M. A., Faith, E. L., Reid, E. K., & Ochs, S. (2019). The potential for automated text evaluation to improve the technical adequacy of written expression curriculum-based measurement. *Learning Disability Quarterly, 42*, 117-128.
- Reschly, A. L., Busch, T. W., Betts, J., Deno, S. L., & Long, J. D. (2009). Curriculum-based measurement oral reading as an indicator of reading achievement: A meta-analysis of the correlational evidence. *Journal of School Psychology, 47*, 427-469.
- Thurstone, L. L. (1927). A law of comparative judgment. *Psychological Review, 34*, 273-286.
- Wilson, J. (2018). Universal screening with automated essay scoring: Evaluating classification accuracy in grades 3 and 4. *Journal of School Psychology, 68*, 19-37.
- Wilson, J., & Czik, A. (2016). Automated essay evaluation software in English Language Arts classrooms: Effects on teacher feedback, student motivation, and writing quality. *Computers & Education, 100*, 94-109.