

Explaining differential performance on academic vocabulary assessments for English language learners (ELLs) using explanatory item response models

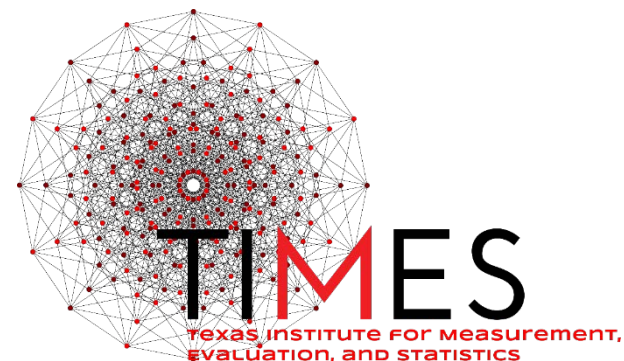
Autumn McIlraith, Paulina Kulesz, David Francis

University of Houston

Joshua Lawrence, Rebecca Knopf

University of Oslo

SSSR, 2019



Acknowledgments

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- Data for the current study comes from the *Word Generation* project (Catherine Snow, <https://wordgen.serpmedia.org/>).
- Thanks to Martin Walczak for help with item coding

Background

- English Language Learners (ELLs) are a growing demographic in U.S. schools.
- ELLs frequently struggle to meet benchmarks for reading proficiency (U.S. Dept of Education, 2017).
- A challenge for assessment
 - Standardized assessments: norming sample typically English-only
 - Differential item functioning?
- For middle school students: Academic Vocabulary is a key ingredient in success across academic disciplines (e.g., Anderson & Freebody, 1981; Coxhead, 2000)



Word Generation study

- Focus: **“all-purpose” academic vocabulary words**, often less explicitly taught, but important for comprehension of discipline-specific texts (Anderson & Freebody, 1981; Coxhead, 2000)
- See Snow, Lawrence, & White (2009) for details of the intervention

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Generating Knowledge of Academic Language Among Urban Middle School Students

Catherine E. Snow, Joshua F. Lawrence, and Claire White
Harvard Graduate School of Education and Strategic Education Research Partnership,
Cambridge, Massachusetts, USA

Word Generation study

- Focus: **“all-purpose” academic vocabulary words**, often less explicitly taught, but important for comprehension of discipline-specific texts (Anderson & Freebody, 1981; Coxhead, 2000)
- See Snow, Lawrence, & White (2009) for details of the intervention
- Students in Grades 6, 7, and 8, in 13 middle schools in a large urban district in California
- **The current study used data from the pre-test (fall semester), prior to the start of the Word Generation intervention.**

Current study

Pre-test data were collected from middle school students, classified into the following categories by the California school district:

(N represents number included in the current analyses)

- **EO:** English-only speakers
- **LEP:** limited English proficiency, continued to qualify for language support
- **IFEP:** initially fluent: proficient in English at the start of the study
- **RFEP:** reclassified as fully English proficient, started as limited

<u>N</u>
3,600
1,851
1,034
3,793
10,278

Current study: Items

- Synonym task
- 50 items on each of two forms, some unique and some shared across forms (81 unique items)
- **Distractors:** semantically, phonologically, or orthographically related, or unrelated

XX. He acquired a pet.

- a. got
- b. trained
- c. lost
- d. adored

XX. We had sufficient food at the party.

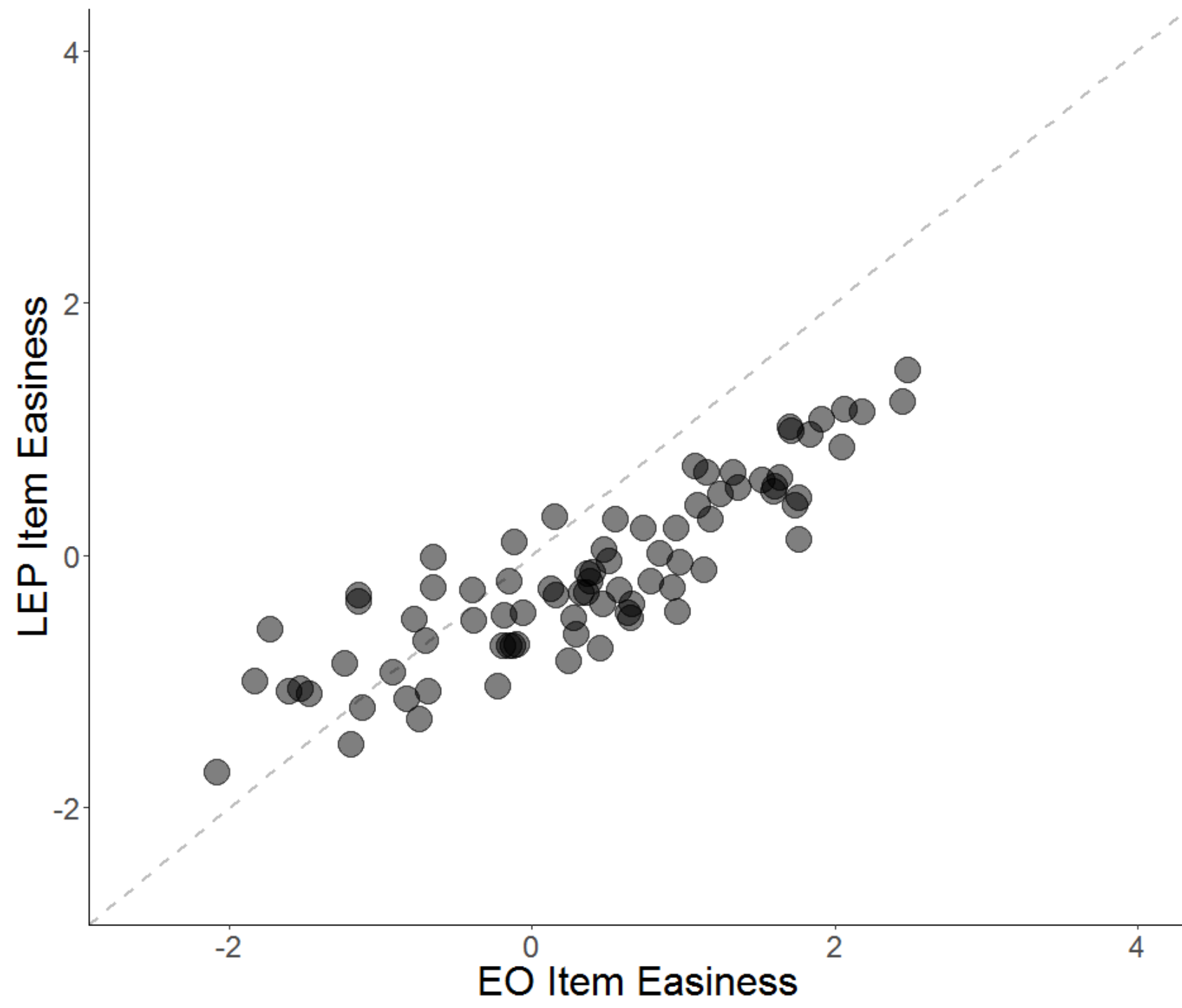
- a. delicious
- b. too much
- c. standard
- d. enough

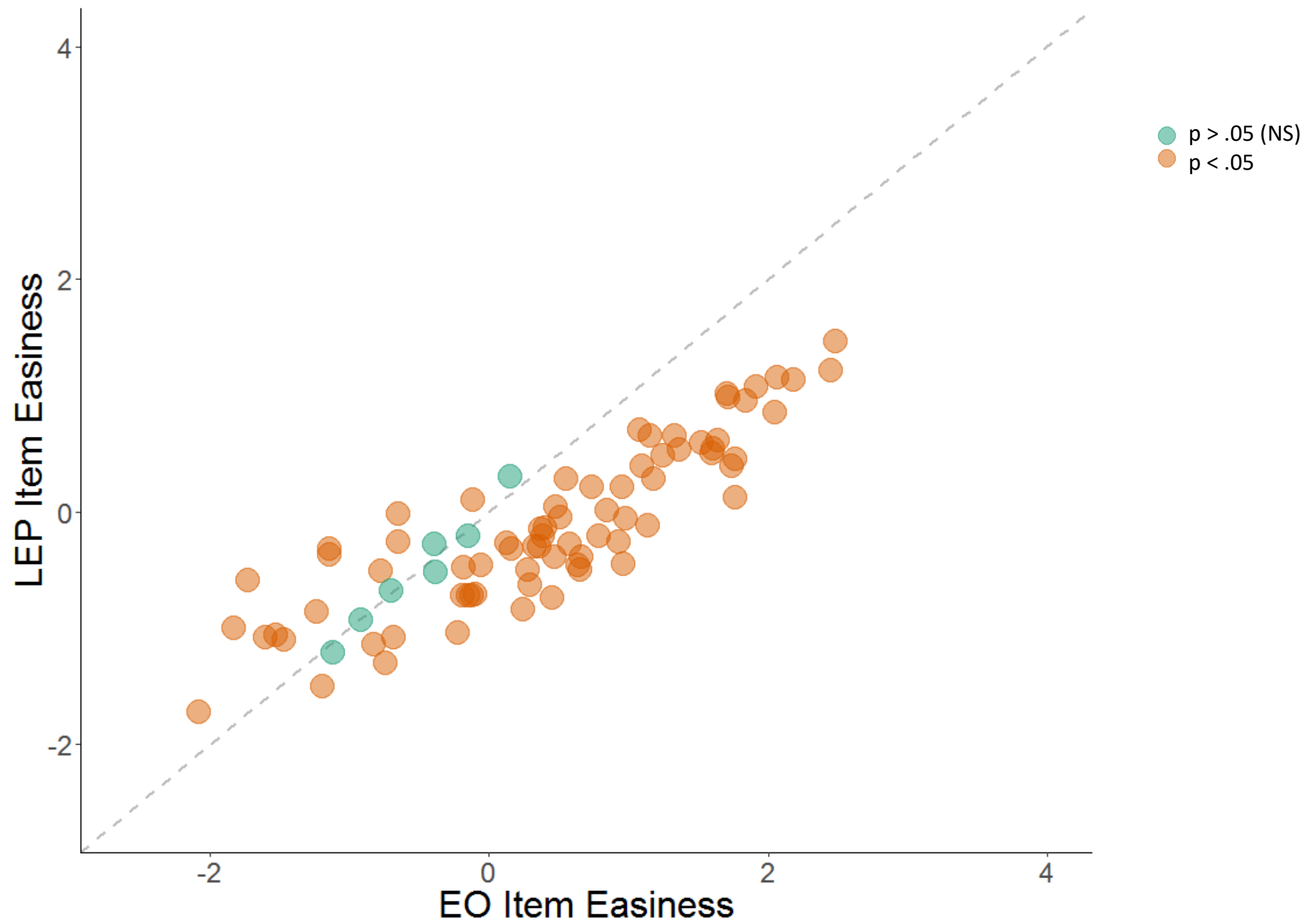


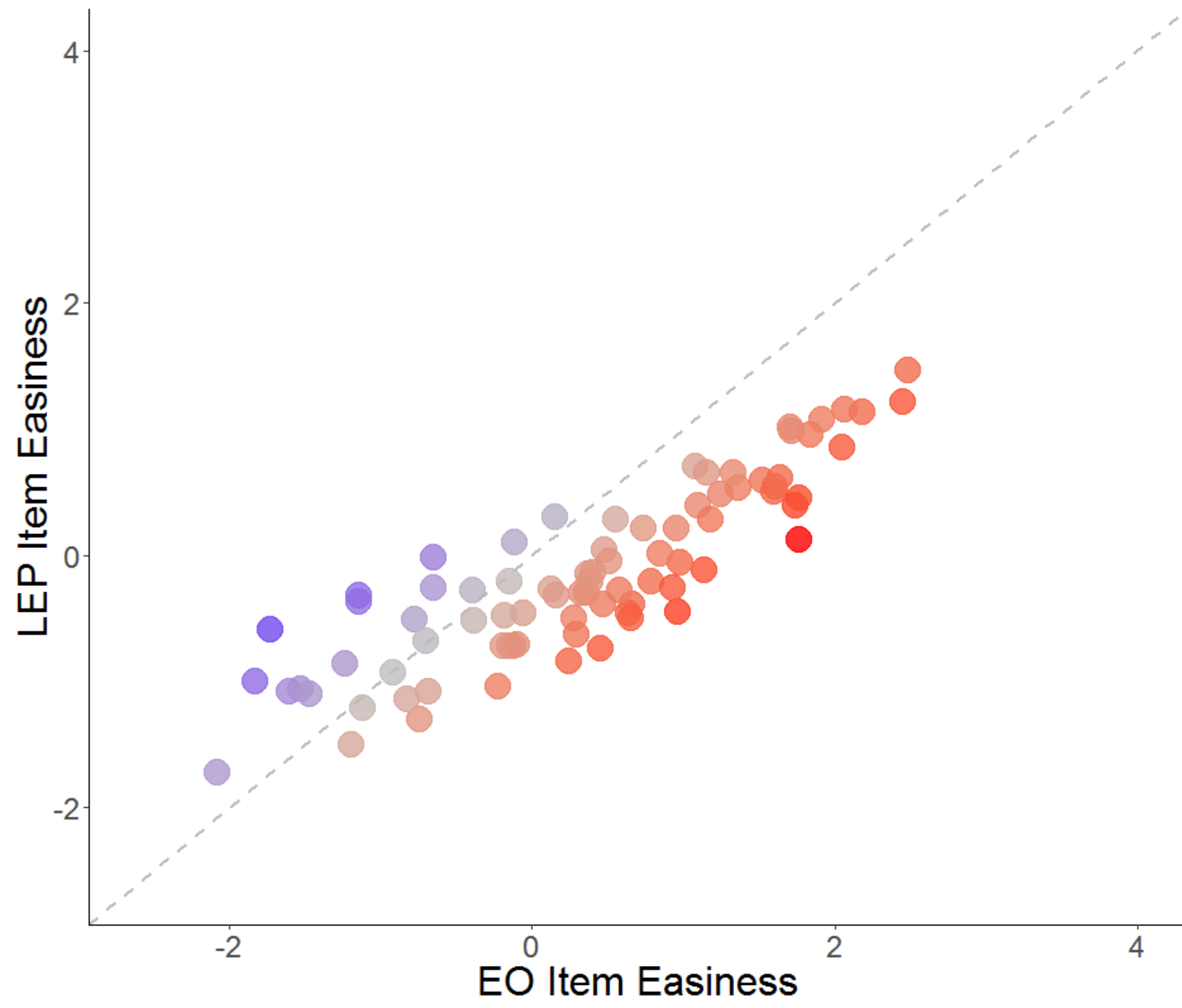
Differential Item Functioning (DIF) analyses

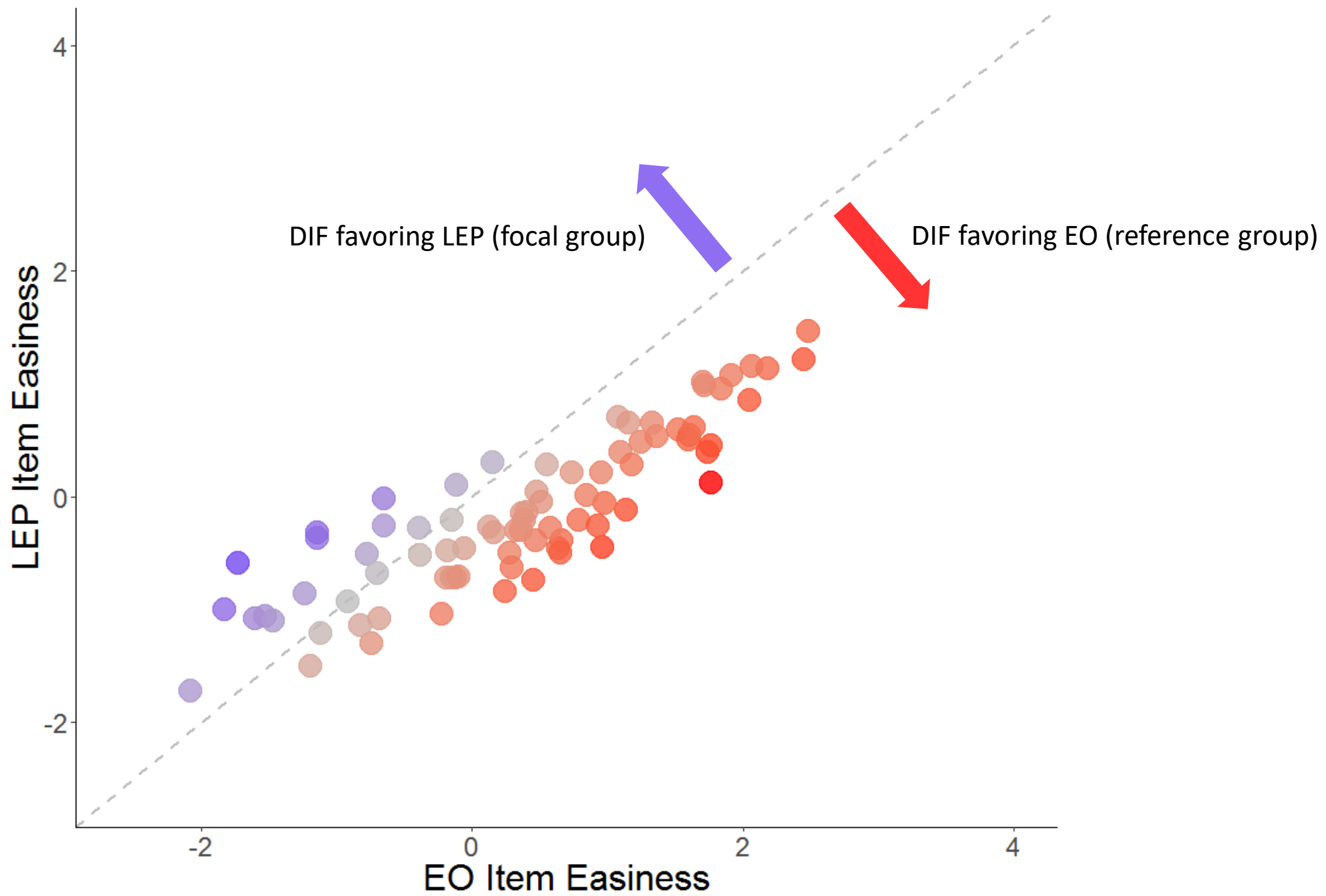
- Item response theory (IRT) approach
- 1PL IRT models (uniform DIF), models estimated in GLIMMIX
- Comparing groups: do two students with the same underlying ability have equal probabilities of getting an item correct?
 - Reference group: EO (English-only)
 - Focal group: LEP (Limited), IFEP (Initially fluent), or RFEP (Reclassified)
- Predicted item “easiness” (higher values = easier items) for each group
- DIF test: difference between the easiness estimates, statistical significance?

DIF Results: EO vs. LEP



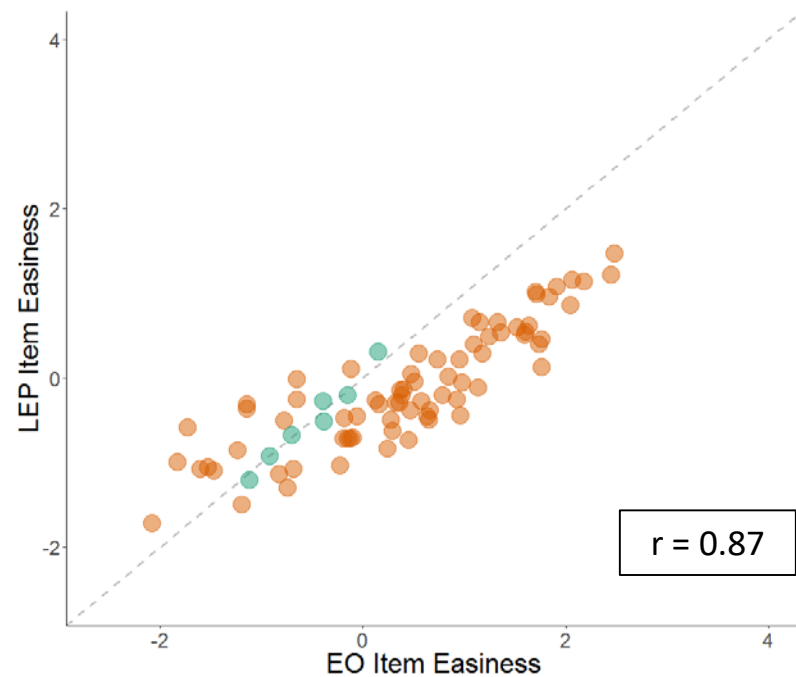




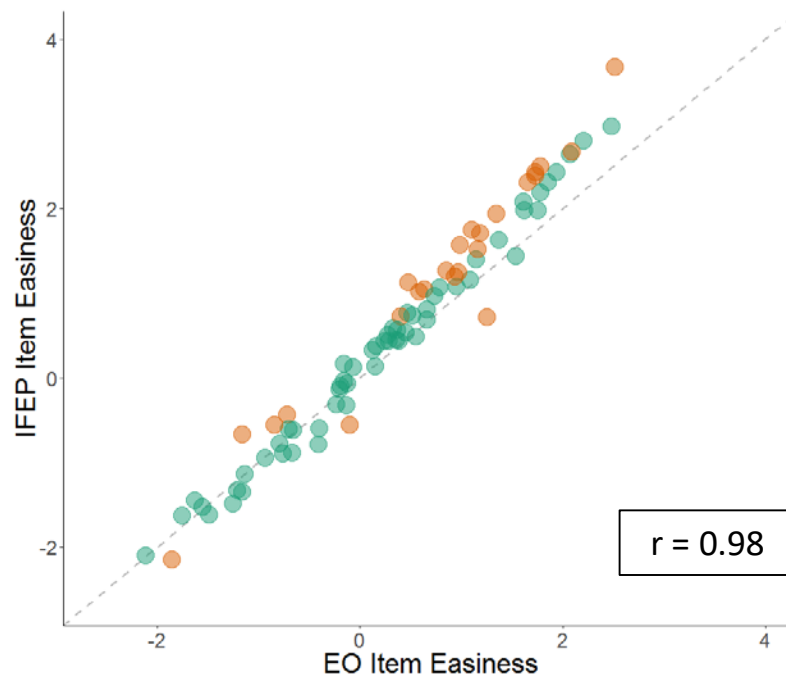


DIF Results

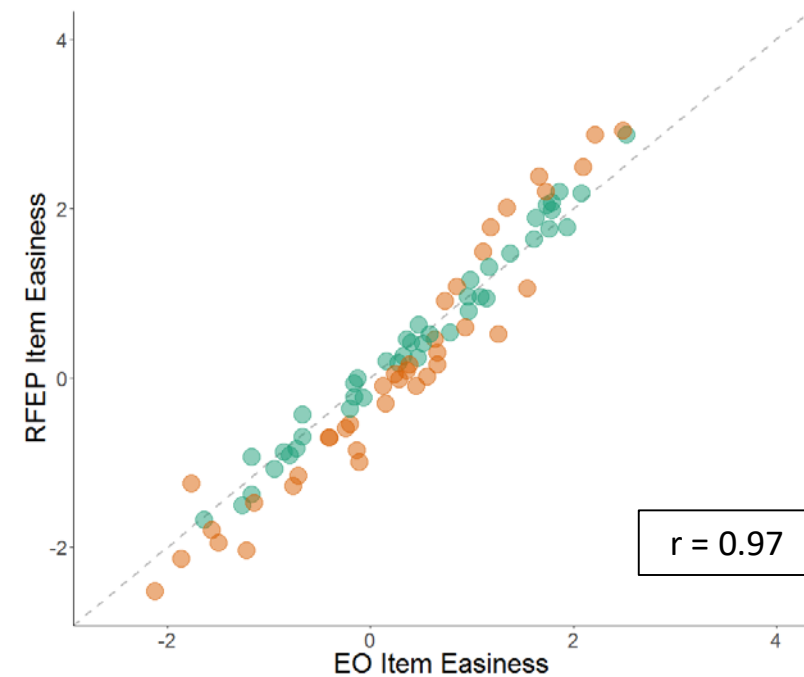
EO vs. LEP



EO vs. IFEP

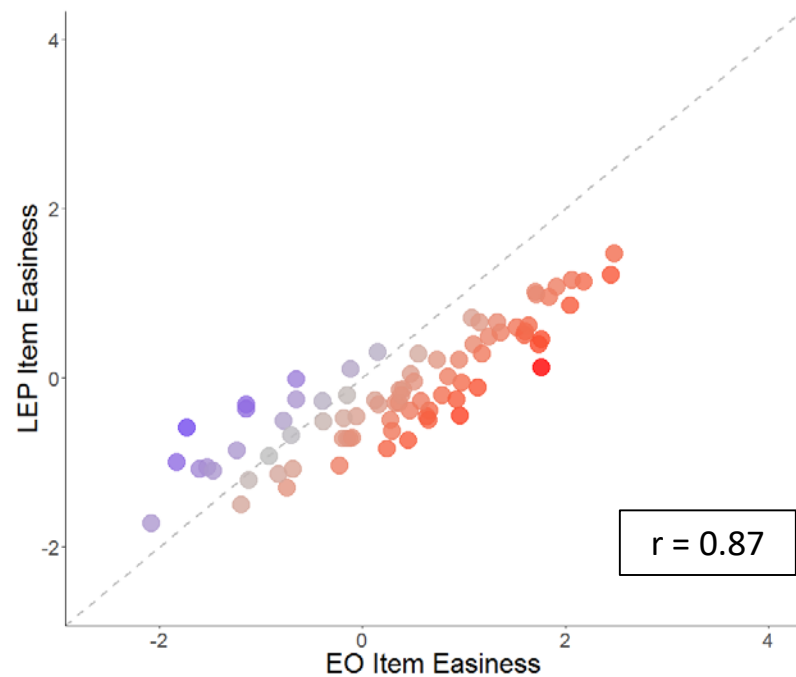


EO vs. RFEP

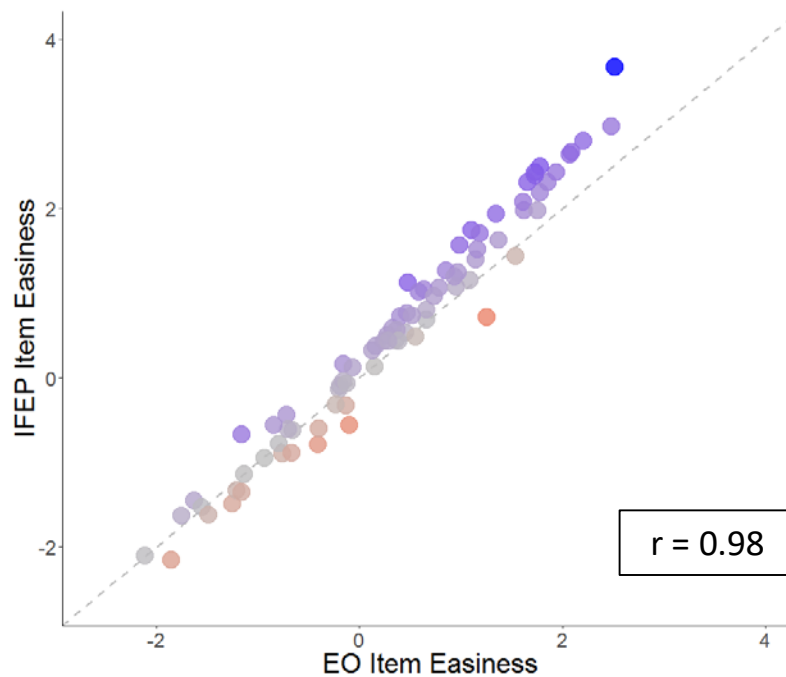


DIF Results

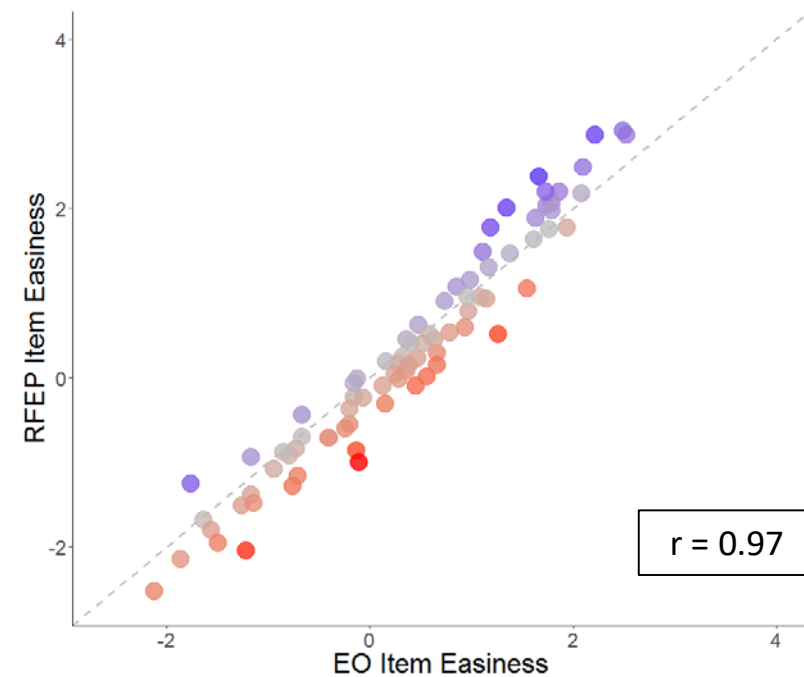
EO vs. LEP



EO vs. IFEP

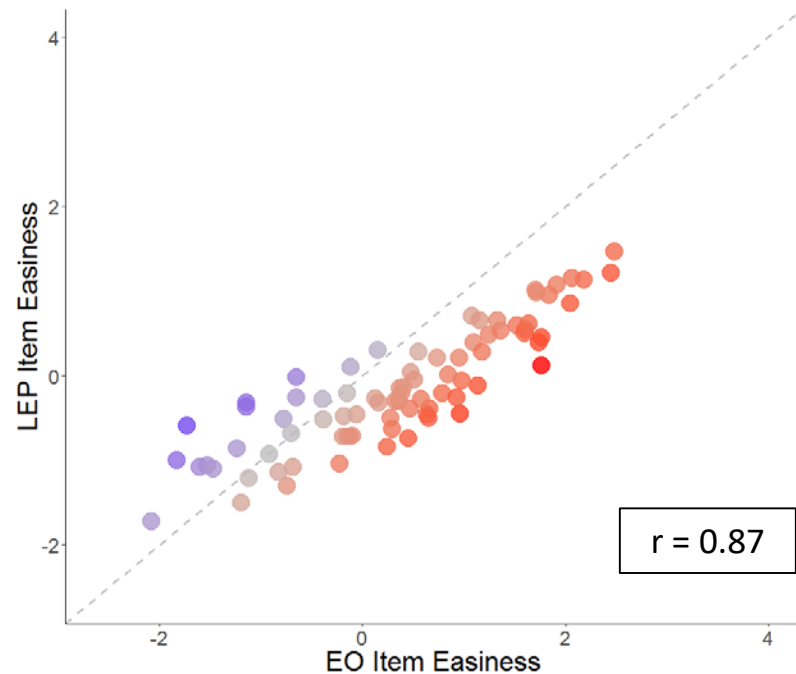


EO vs. RFEP

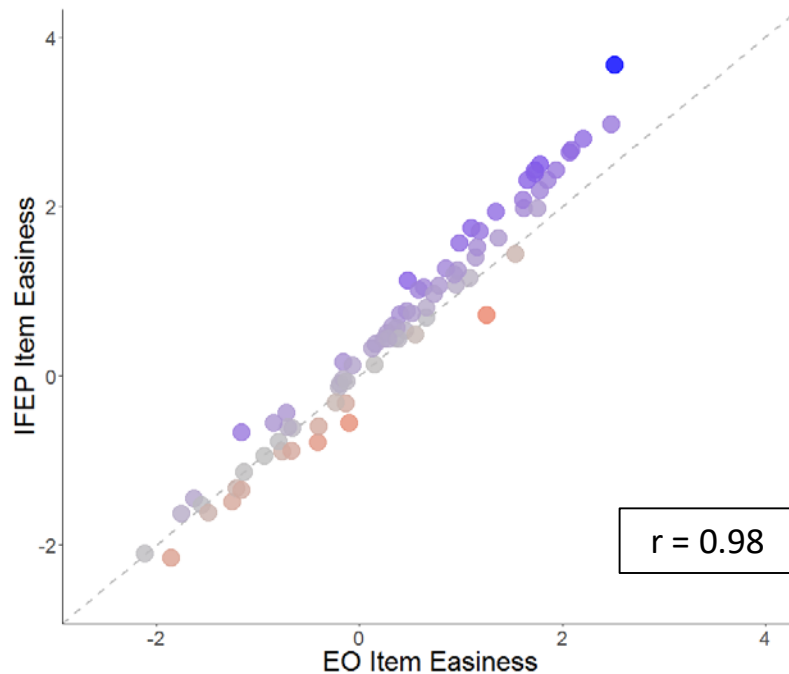


DIF Results

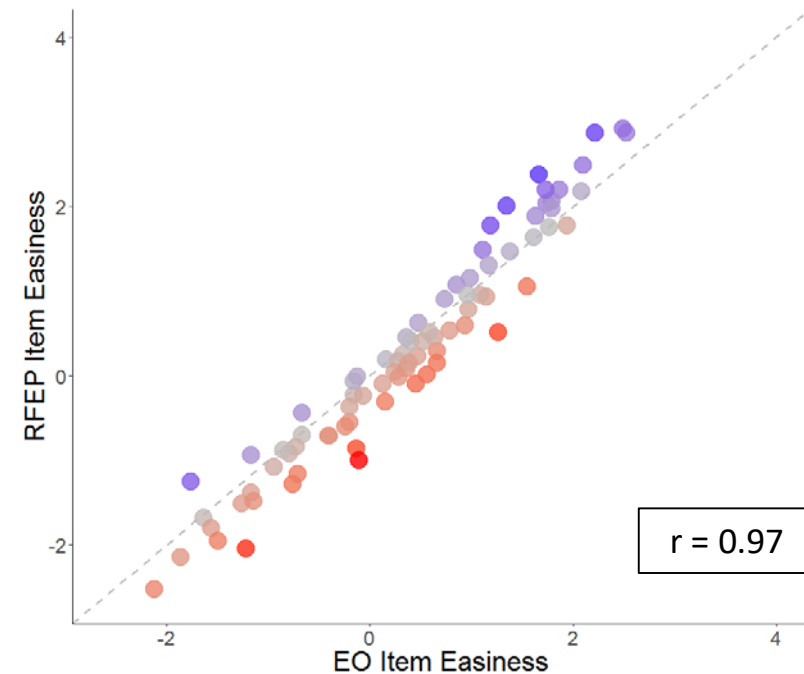
EO vs. LEP



EO vs. IFEP



EO vs. RFEP



Explanatory IRT (eIRT) and other analyses

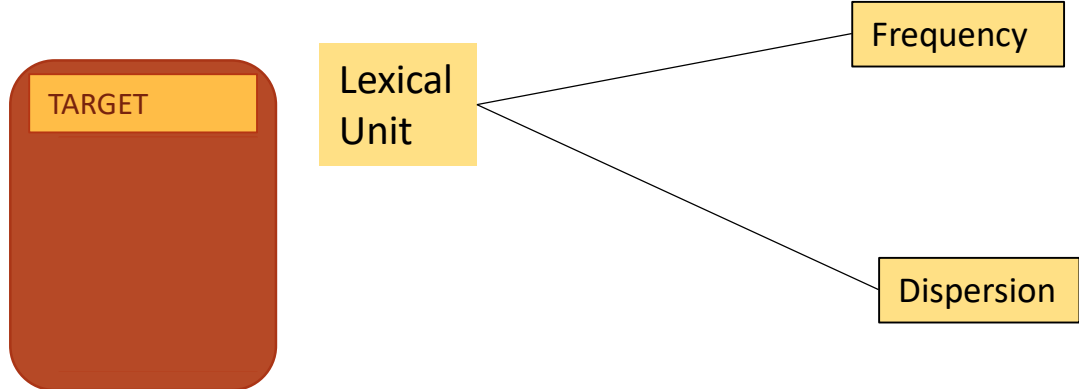
Item characteristics used as predictors



XX. He acquired a pet.

- a. got
- b. trained
- c. lost
- d. adored







Lexical
Unit

Frequency

Word frequency (Zeno, zipfian transform)

Word Frequency (Brown corpus, log transform)

Word Frequency (HAL corpus, log transform)

Dispersion



Lexical
Unit

Frequency

Word frequency (Zeno, zipfian transform)

Word Frequency (Brown corpus, log transform)

Word Frequency (HAL corpus, log transform)

First year when word appeared

Dispersion

Contextual Diversity (Adelman)

Contextual Diversity (Subtlex)

Number of content areas where word appears (Zeno)



Lexical
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Phonological

Orthographic

Semantic



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Phonological

Number of phonemes

Number of syllables

Number of phonological neighbors

Phonologic Levenshtein distance 20

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Number of phonographic neighbors
Number of letters
Orthographic Levenshtein distance 20
Number of orthographic neighbors

Semantic

Bigram letter average frequency



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Bigram letter average frequency

Semantic

Number of morphemes
Number of senses and meanings across parts of speech (Wordnet)
Semantic diversity of neighbors (Hoffman)

Explanatory IRT (eIRT) and other analyses

Item characteristics used as predictors

eIRT approach: binary 1/0 (correct/incorrect) responses modeled as outcome

Supplemented with **regression approach:** Model parameters from GLIMMIX as outcomes

- EO item easiness
- Focal group item easiness
- DIF
- **Stepwise regression**
- **Best subsets regression**



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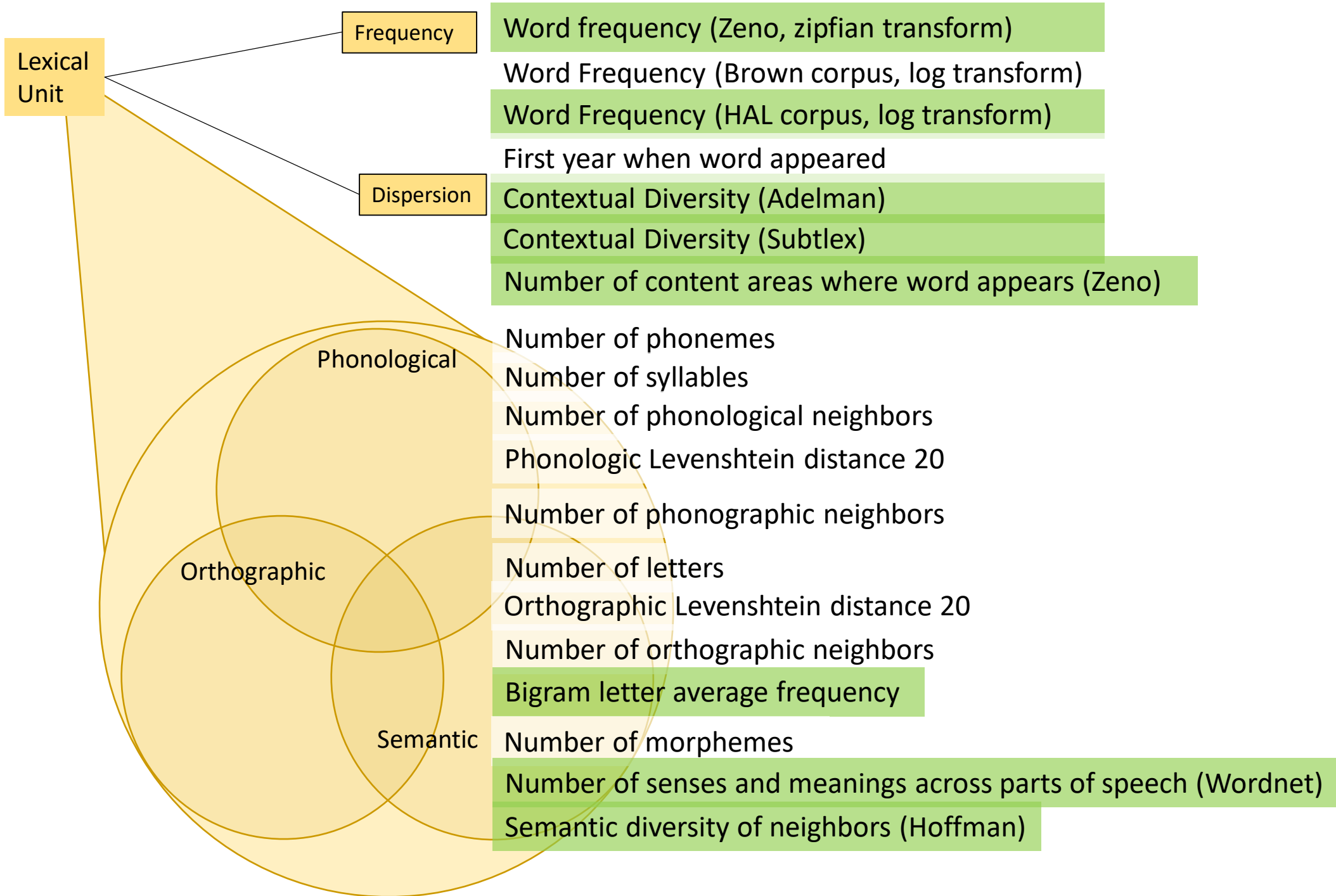
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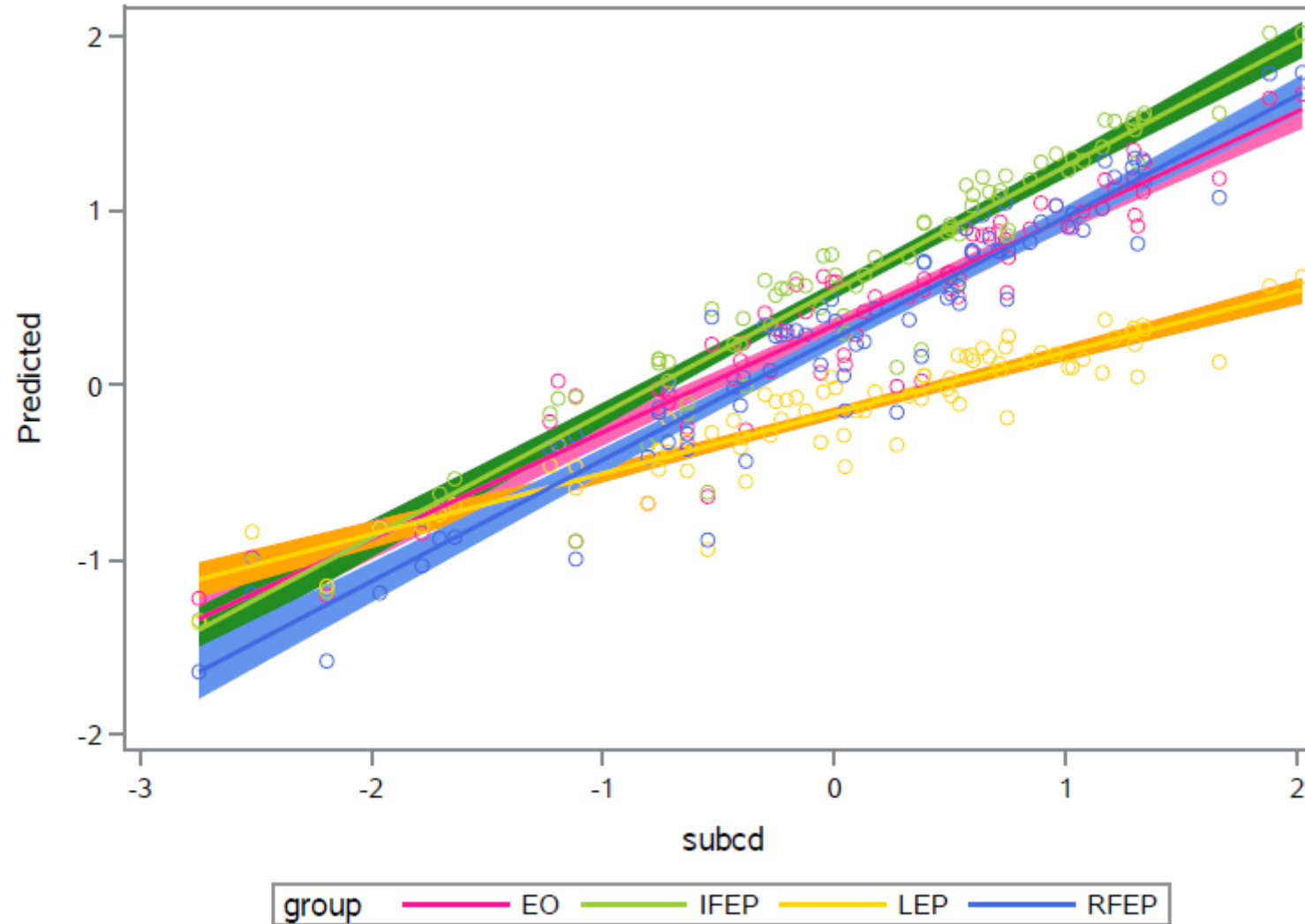
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eIRT: contextual diversity*group





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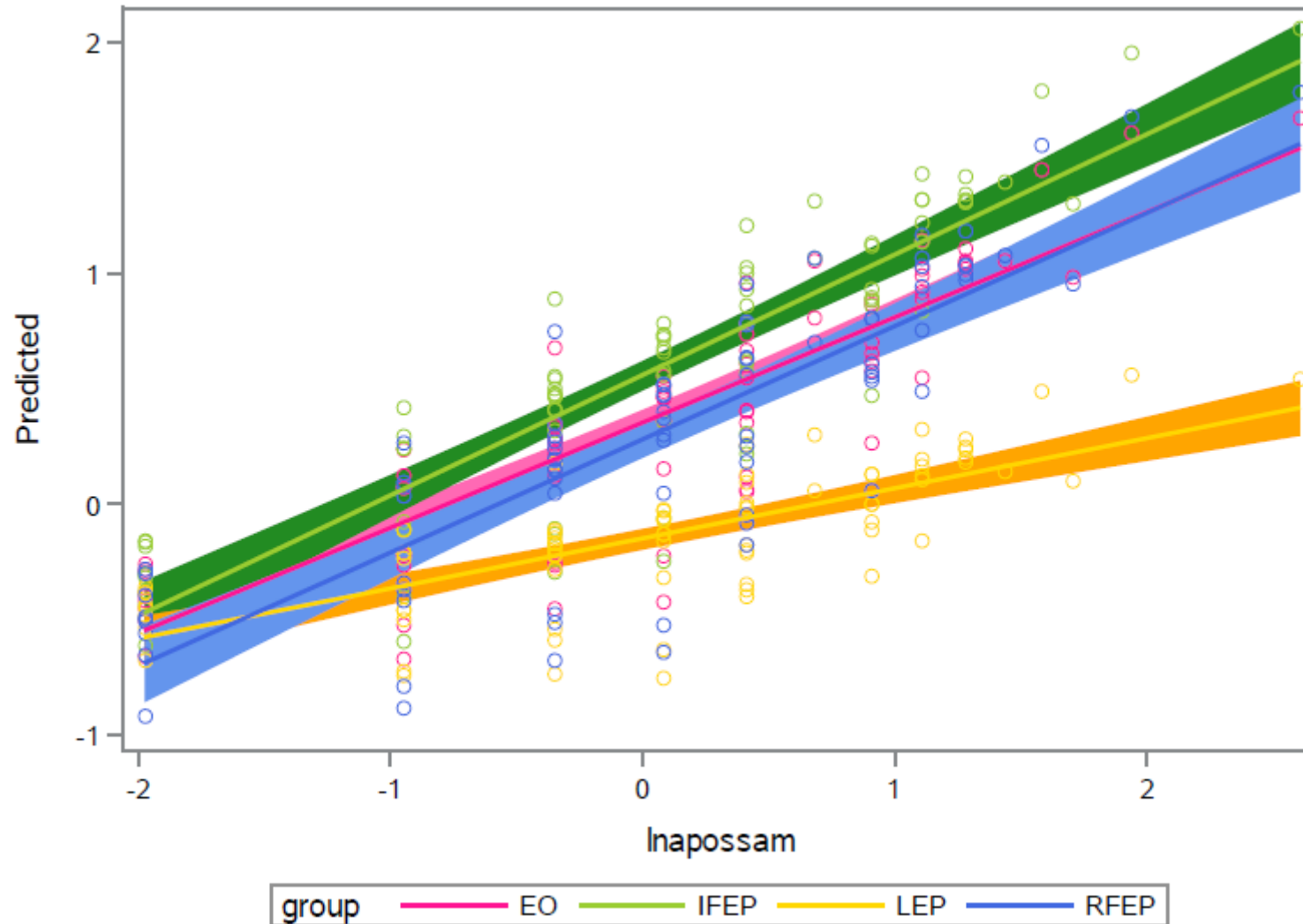
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eIRT: meanings & senses*group

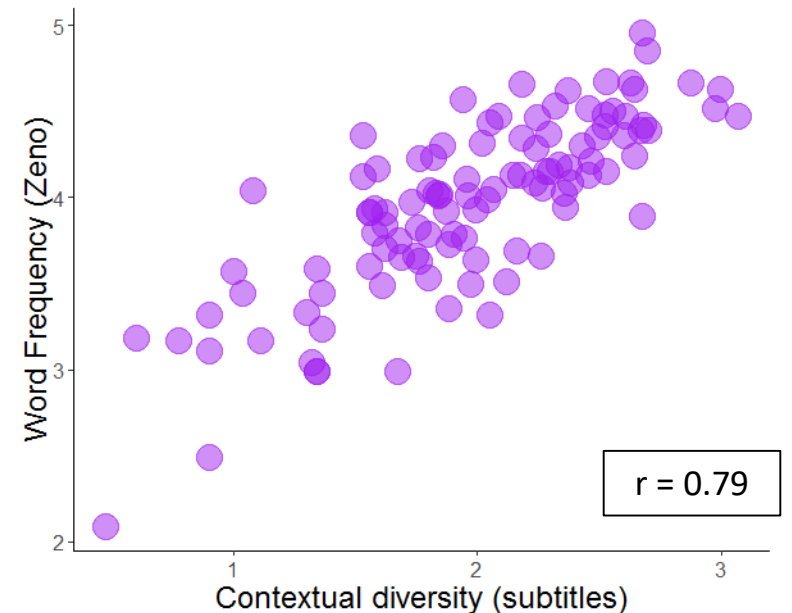


Converging results across analyses

- **Contextual diversity (subtitles): number of documents in the corpus containing a given word (corpus of subtitles from movies and television)**
 - Single strongest predictor of item easiness for all groups.
 - Positive relation: greater contextual diversity is associated with easier items
 - Correlated with some other predictors (e.g., frequency), often the only significant unique predictor in models with multiple predictors
 - eIRT: significant interaction of contextual diversity*group
- **Number of meanings and senses (WordNet): combined meanings and senses across parts of speech**
 - Greater number of meanings and senses associated with easier items
 - eIRT: significant interaction of meanings&senses*group
- **Word frequency:** higher frequency associated with easier items

Discussion

- Frequency vs. Contextual diversity: where we encounter a word vs. how often
 - Adelman, Brown, & Quesada, 2006
- More meanings & senses: easier items
- How many predictors are enough?
- IFEP & RFEP students: show similar pattern to EO students
- LEP: weaker relations between predictors & item easiness
- Heterogeneity among ELLs



Still exploring...

- Part of speech
- Word concreteness
- Differential distractor functioning
- Carrier sentence
- Characteristics of Key
- Similarity between Key & Target
- Similarities between responses
- Student characteristics

XX. We had sufficient food at the party.

- a. delicious
- b. too much
- c. standard
- d. enough

Thank you!

<http://172.27.244.67//sample-apps/alm/>



Autumn McIlraith

autumn.mcilraith@times.uh.edu

Exploring DIF: ITEM PREDICTORS

Each observation represents a single item from the Word Generation Academic Vocabulary assessment.
GLIMMIX parameters are from a DIF analysis of 6th-8th graders.

EO: English-Only

LEP: Limited English Proficiency

IFEP: Initially Fluent English Proficiency

RFEP: Reclassified Fluent English Proficiency

Select variable for y-axis

GLIMMIX: LEP item easiness

Select variable for x-axis

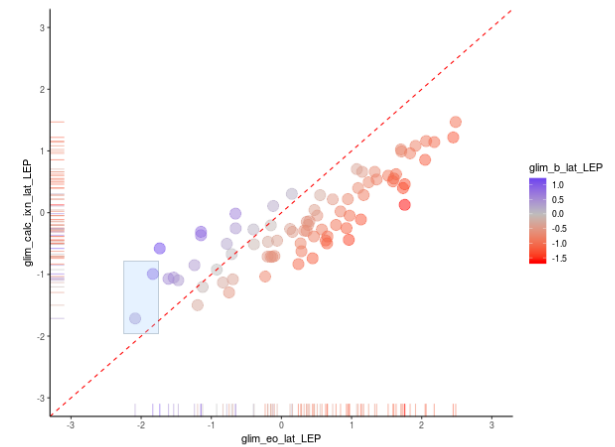
GLIMMIX: EO item easiness

Color by:

GLIMMIX: item*group unidif (w/ability) LEP

☐ Show reference lines at zero

☒ Show 1:1 reference line



Correlation = 0.872

Click and drag in the plot area to select observations.

new_item_id	text	stem_text	key_text
W010_052	cohesion	the essay needed cohesion	consistency
W010_062	enforced	the teacher enforced the rule	imposed

This app was created using the Shiny package in R. For more information about Shiny, go to <https://shiny.rstudio.com/>.