Individual variation and the roles of L1 and proficiency in the longitudinal L2 development of English grammatical morphemes

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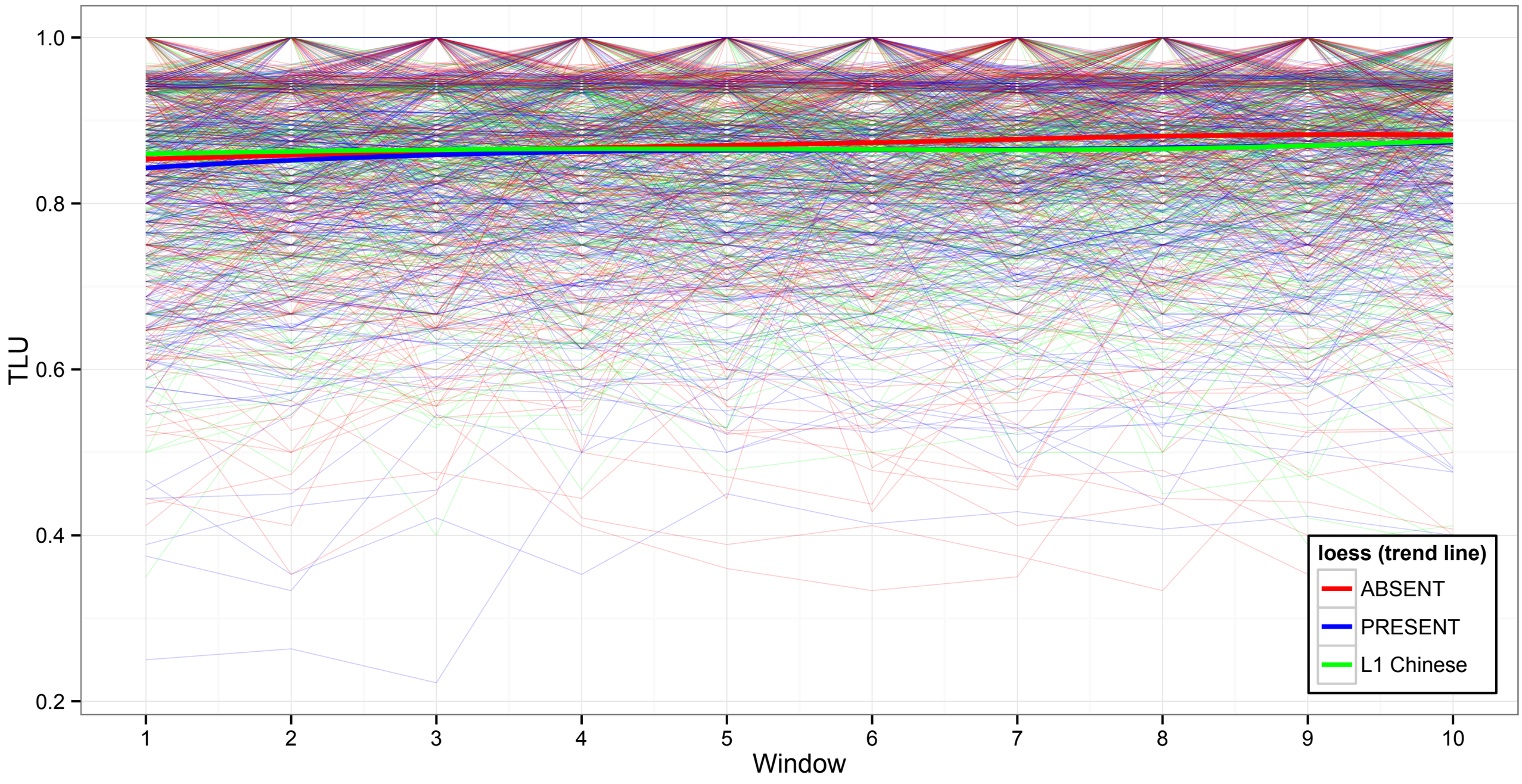
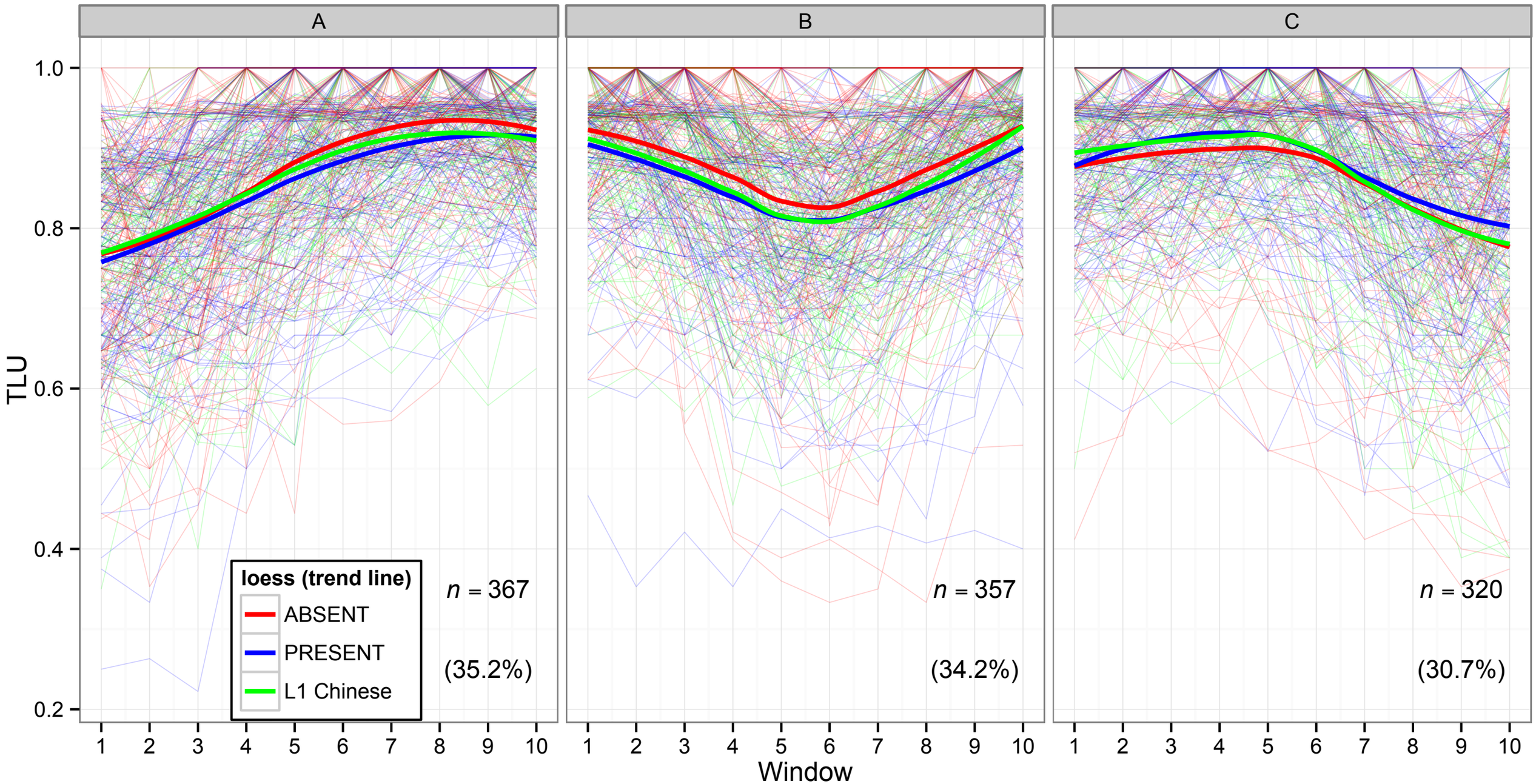
Background

- Describing and explaining individual variation in longitudinal development are critical for a theory of L2 development.
- In order to tackle the issue, we need large empirical data.
- With the advent of large-scale learner corpora, we now have enough data to address the issue.
- Few studies have investigated longitudinal development at a large scale.

Longitudinal Development of Articles



Clustered Development



Aims of the Study

- Investigate whether learners' L1 backgrounds and proficiency affect the longitudinal accuracy transition of L2 English grammatical morphemes.
- Reveal inter-learner variation.

Predictors

- L1 influence is pervasive in L2 acquisition (Jarvis & Pavlenko, 2007). The same is true for the L2 acquisition of English grammatical morphemes (Luk & Shirai, 2009; Murakami, 2013).
- The effect of proficiency on accuracy is prevalent (Thewissen, 2013).
- Given these, the two variables may affect the within-learner developmental patterns as well.

Target Morphemes

- articles
- past tense *-ed*
- plural *-s*

Target L1 Groups

- Typologically diverse L1s
  - Japanese
  - Korean
  - Spanish
  - Russian
  - Turkish
  - German
  - French
  - Brazilian-Portuguese
  - Mandarine-Chinese
  - Italian

EF-Cambridge Open Language Database (EFCamDat)

- Essays written at Englishtown, the online school of Education First
- 16 Lessons × 8 Units (A1-C2 in CEFR)
- Each student writes one essay per unit
- Teachers' feedback available on some essays (≒ error tags)
- 140,000 essays by 52,000 learners, totaling 10 million words
- Available at http://corpus.mml.cam.ac.uk/efcamdat/

Accuracy Measure

TLU (Target-Like Use) score was used

$$\text{TLU score} = \frac{\text{number of correct suppliance}}{\text{number of obligatory contexts} + \text{number of incorrect suppliance}}$$

Two Types of Regression Models

- Mixed-effects model
  - Take into account the dependency of data within individual learners
- Generalised additive model
  - Take into account the nonlinearity of the effects of proficiency
- See if the two analyses converge

Mixed-Effects Model

- A mixed-effects logistic regression model
- Dependent variable: TLU
- Independent variables
  - L1
  - Morpheme
  - Proficiency (standardised)
  - Essay number (standardised)
  - Their two-way interactions
- Random-effects
  - Learner (random-intercept)
  - Morpheme (random-slope)
  - Essay number (random-slope)

Multi-Model Inference

- Compare the following models in order to test the effects of L1 and proficiency.
- Model 1: Maximal model with the full structure just described
- Model 2: Model 1 - EssayNum-L1 interaction
- Model 3: Model 1 - EssayNum-Proficiency interaction
- Model 4: Model 1 - EssayNum-Morpheme interaction
- Null Model: Random-effects only

Model Selection

		Likelihood ratio test against			
Model	AIC	Model 1		Null Model	
Model 1	72,607			$\chi^2(54) = 2462.675$	$p < 0.001$
Model 2	72,603	$\chi^2(9) = 14.210$	$p = 0.115$	$\chi^2(45) = 2448.465$	$p < 0.001$
Model 3	72,614	$\chi^2(1) = 9.225$	$p = 0.002$	$\chi^2(53) = 2453.450$	$p < 0.001$
Model 4	72,614	$\chi^2(2) = 11.256$	$p = 0.004$	$\chi^2(52) = 2451.419$	$p < 0.001$
Null Model	74,961	$\chi^2(54) = 2462.675$	$p < 0.001$		

Model	Model description
Model 1	Maximal model
Model 2	EssayNum–L1 interaction excluded
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Null Model	No fixed-effects

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Random-Effects

		Model 2	Null Model
Factor	Random Effects	SD	SD
Learner	Intercept	0.501	0.758
Morpheme			
	Past tense *-ed*	0.919	1.140
	Plural *-s*	0.510	1.071
EssayNum.Standardized		0.297	0.327

Random-Effects

The model without any predictors

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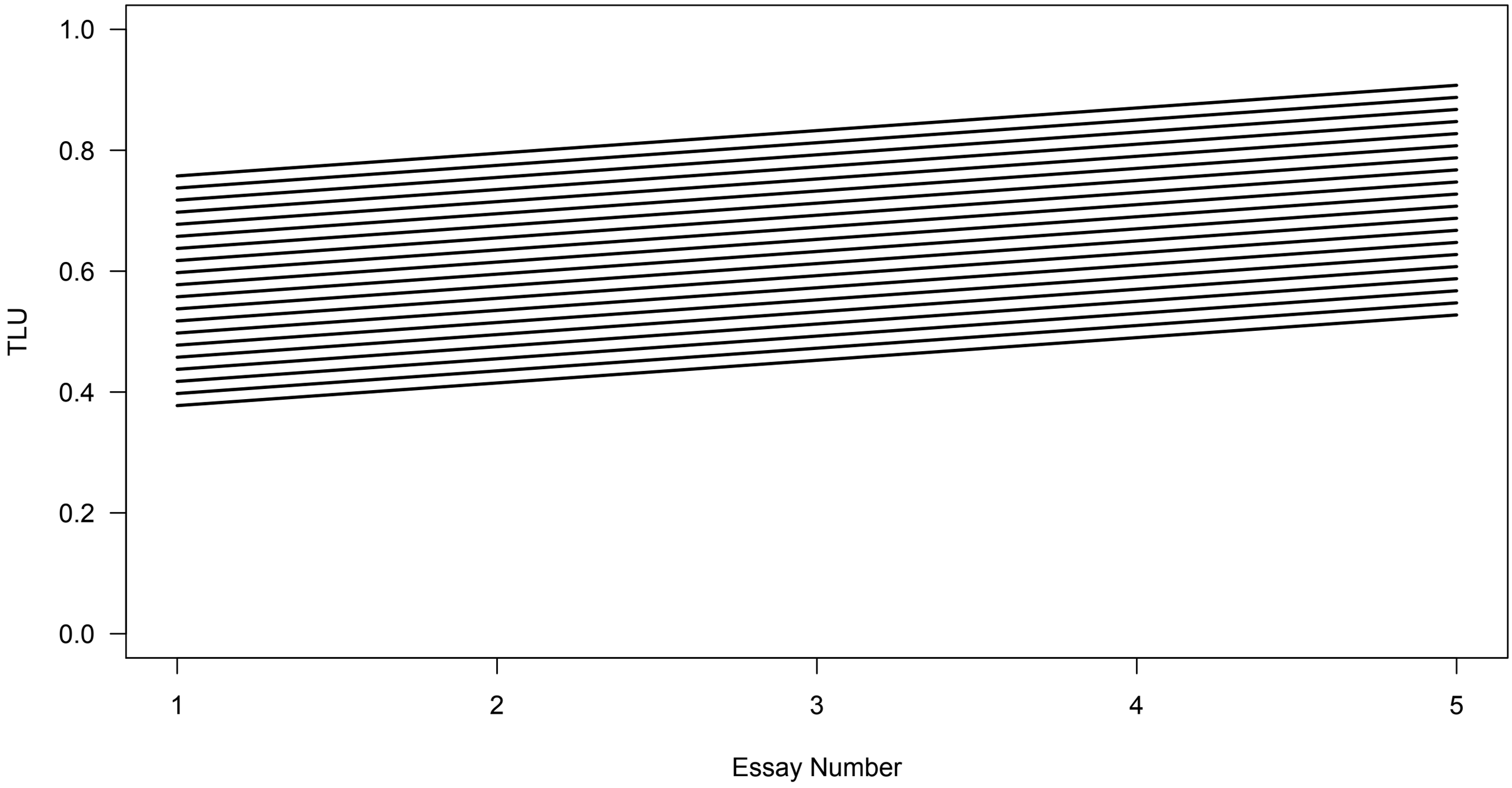
Demonstration of Random-Intercept



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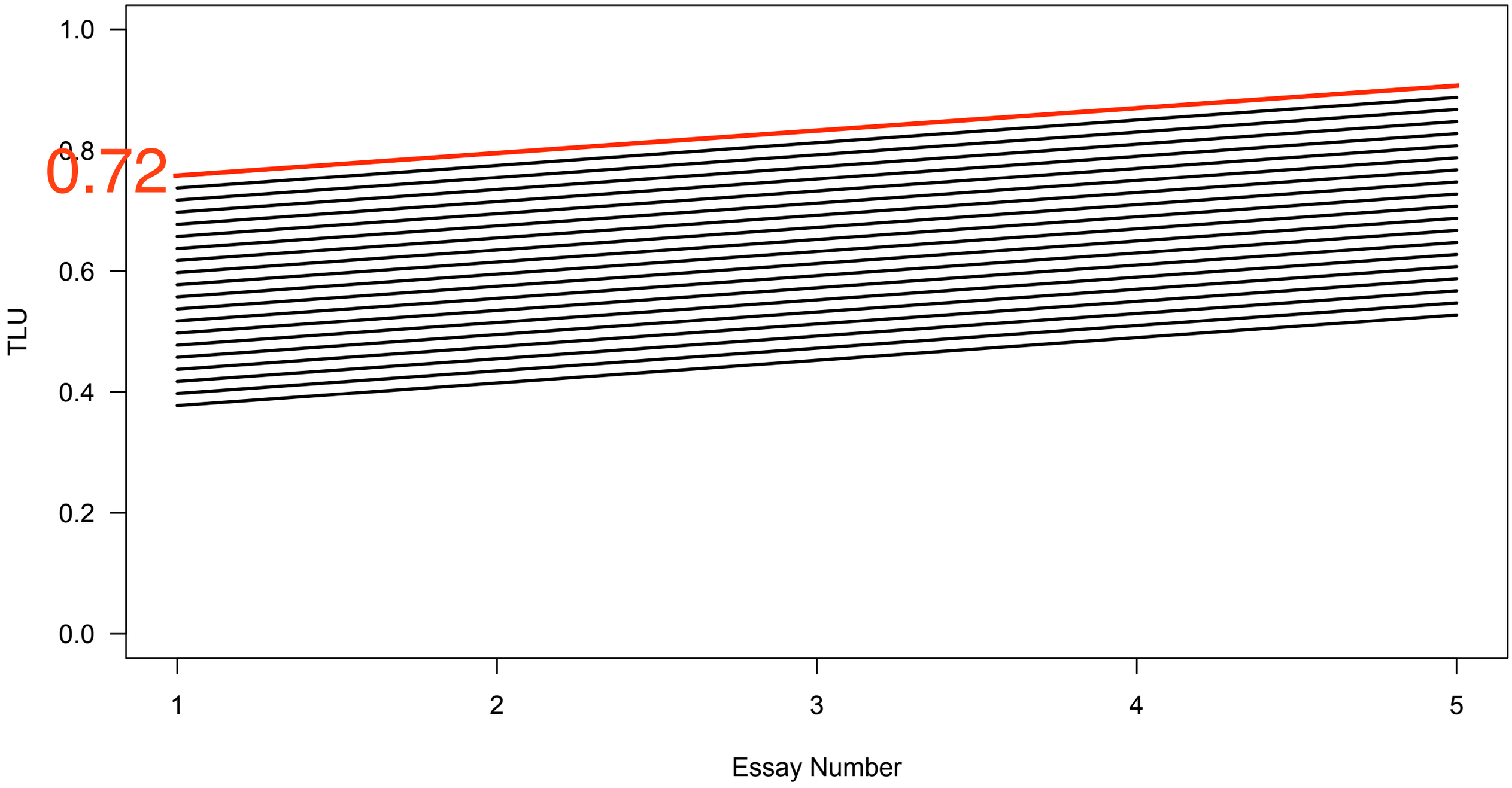

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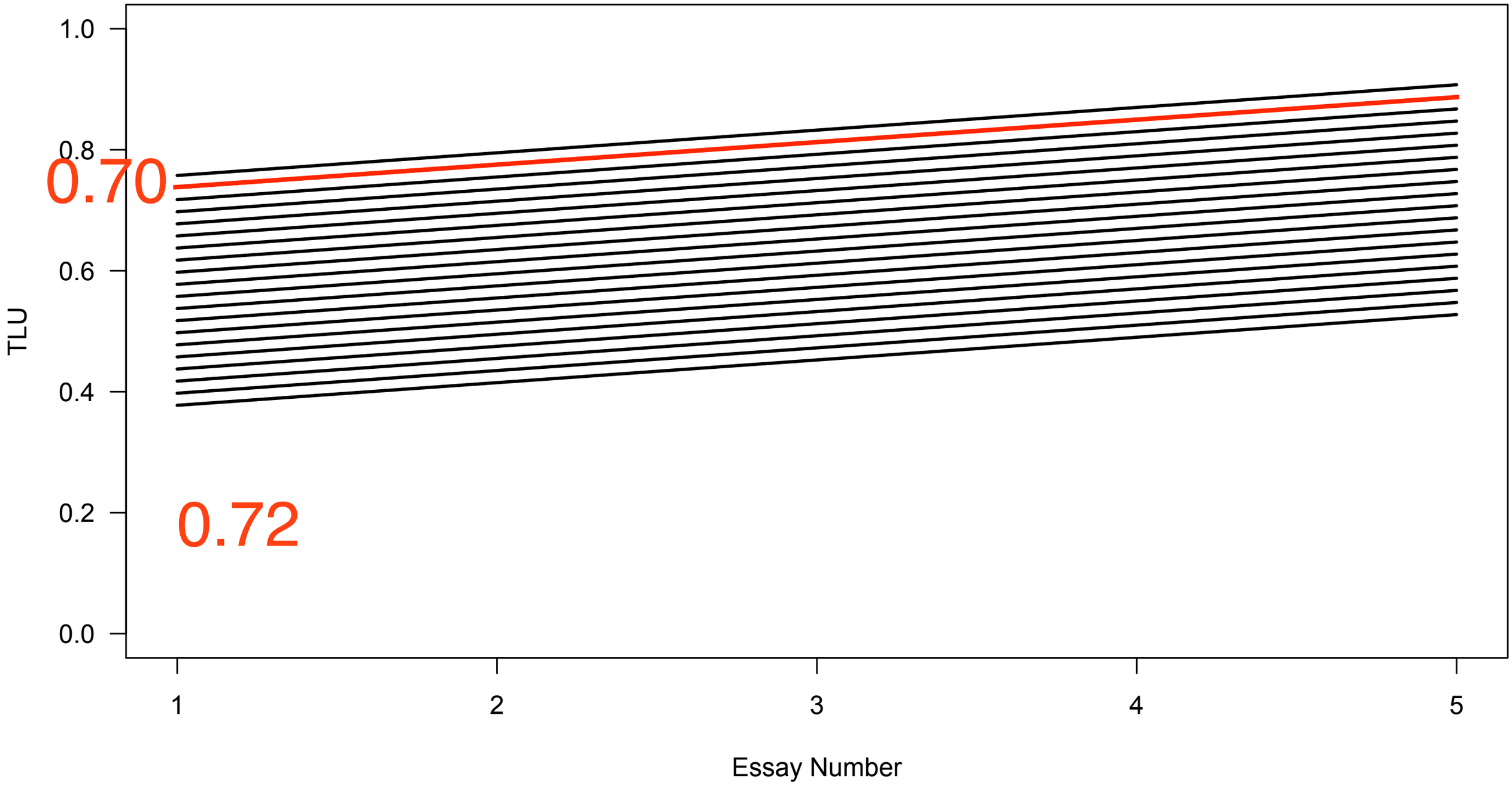

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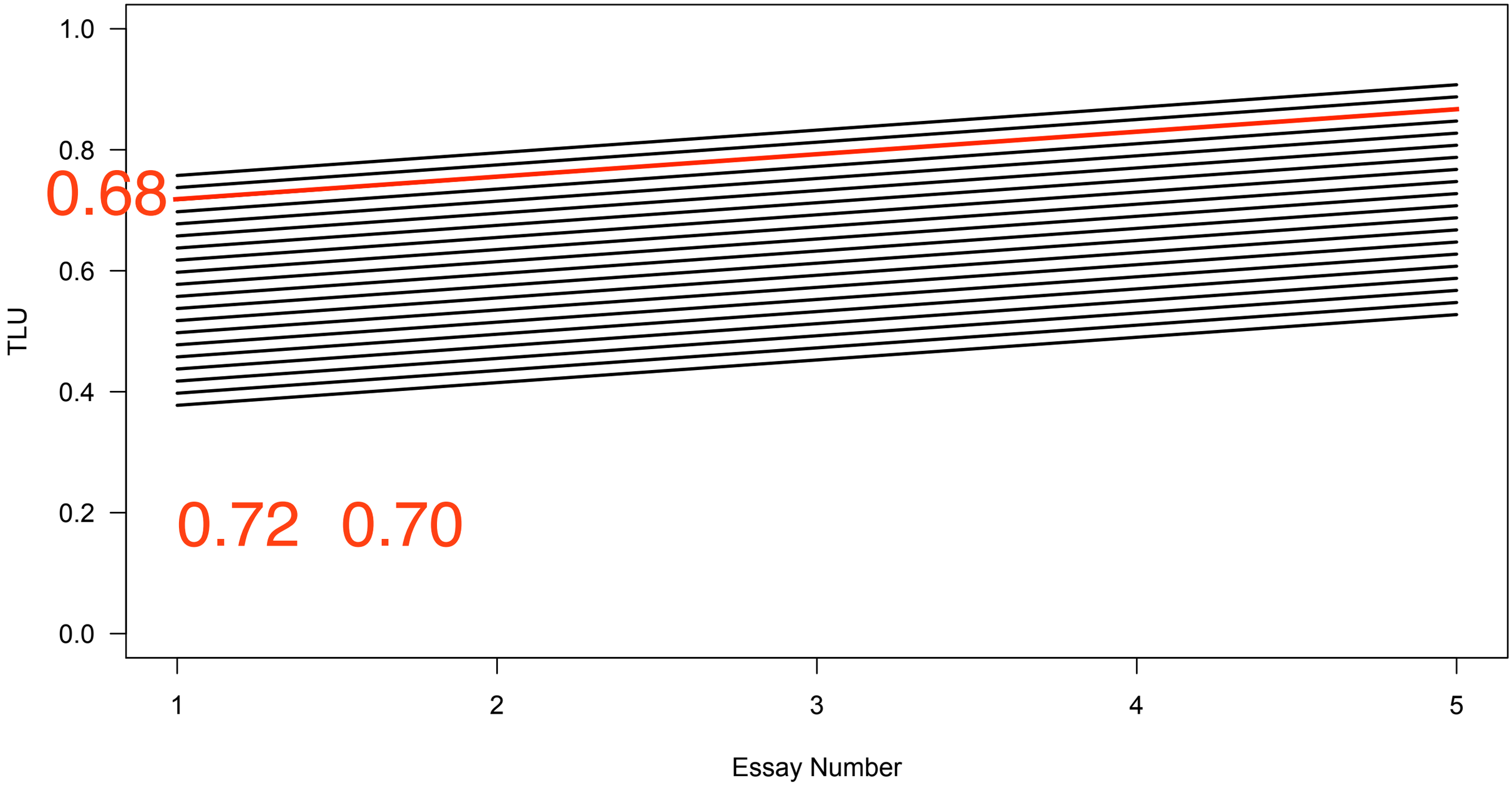

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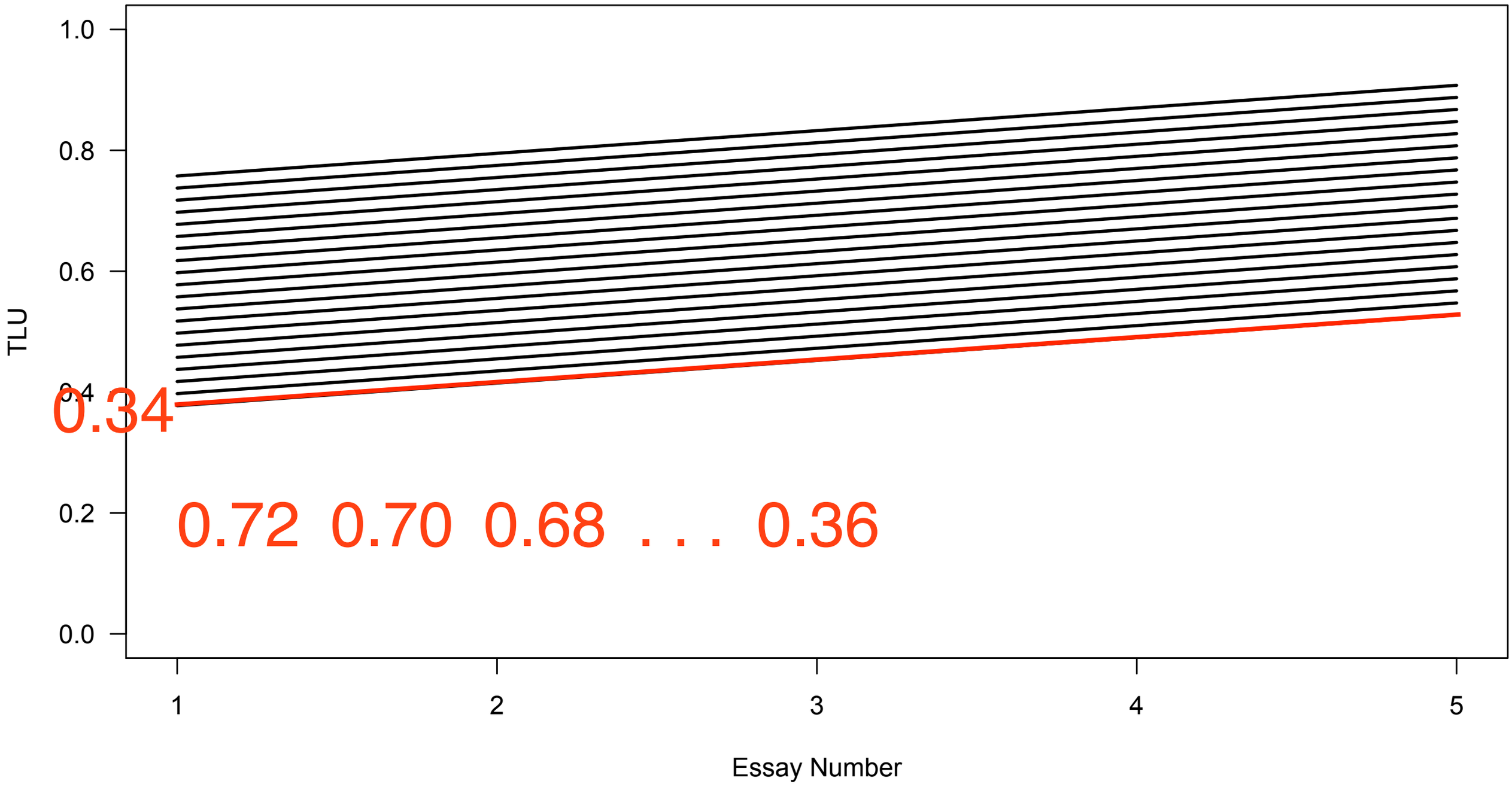

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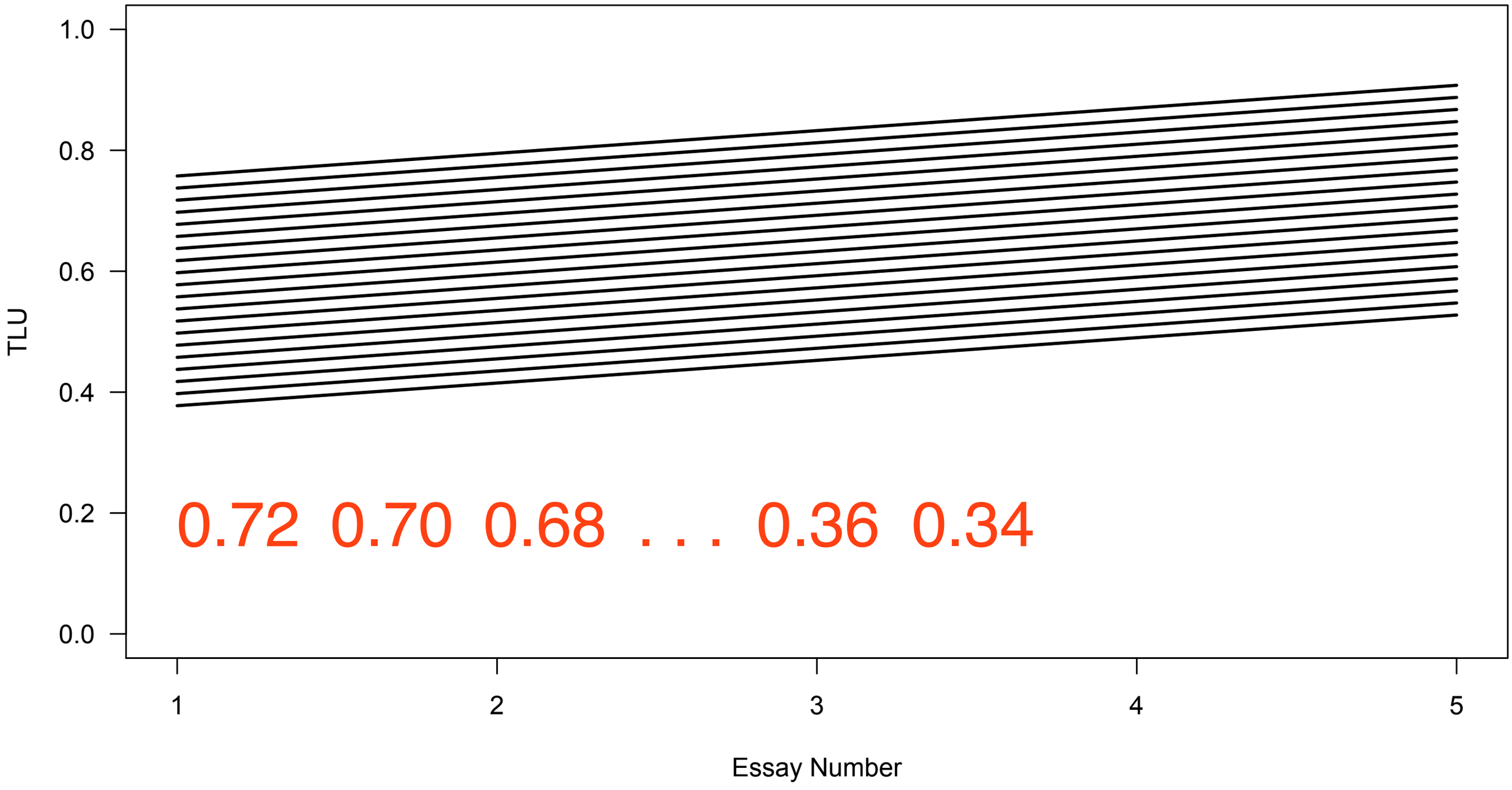

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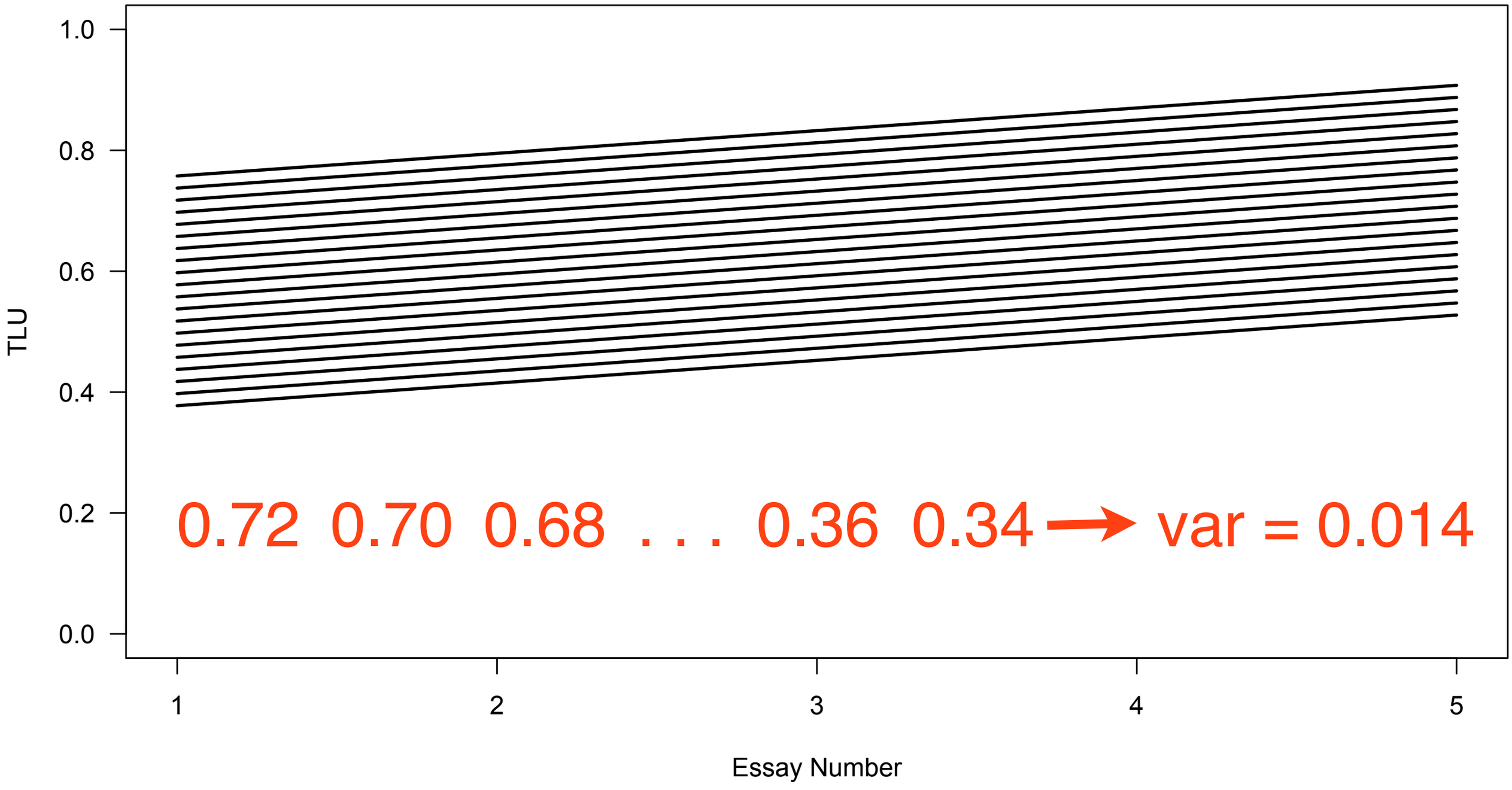

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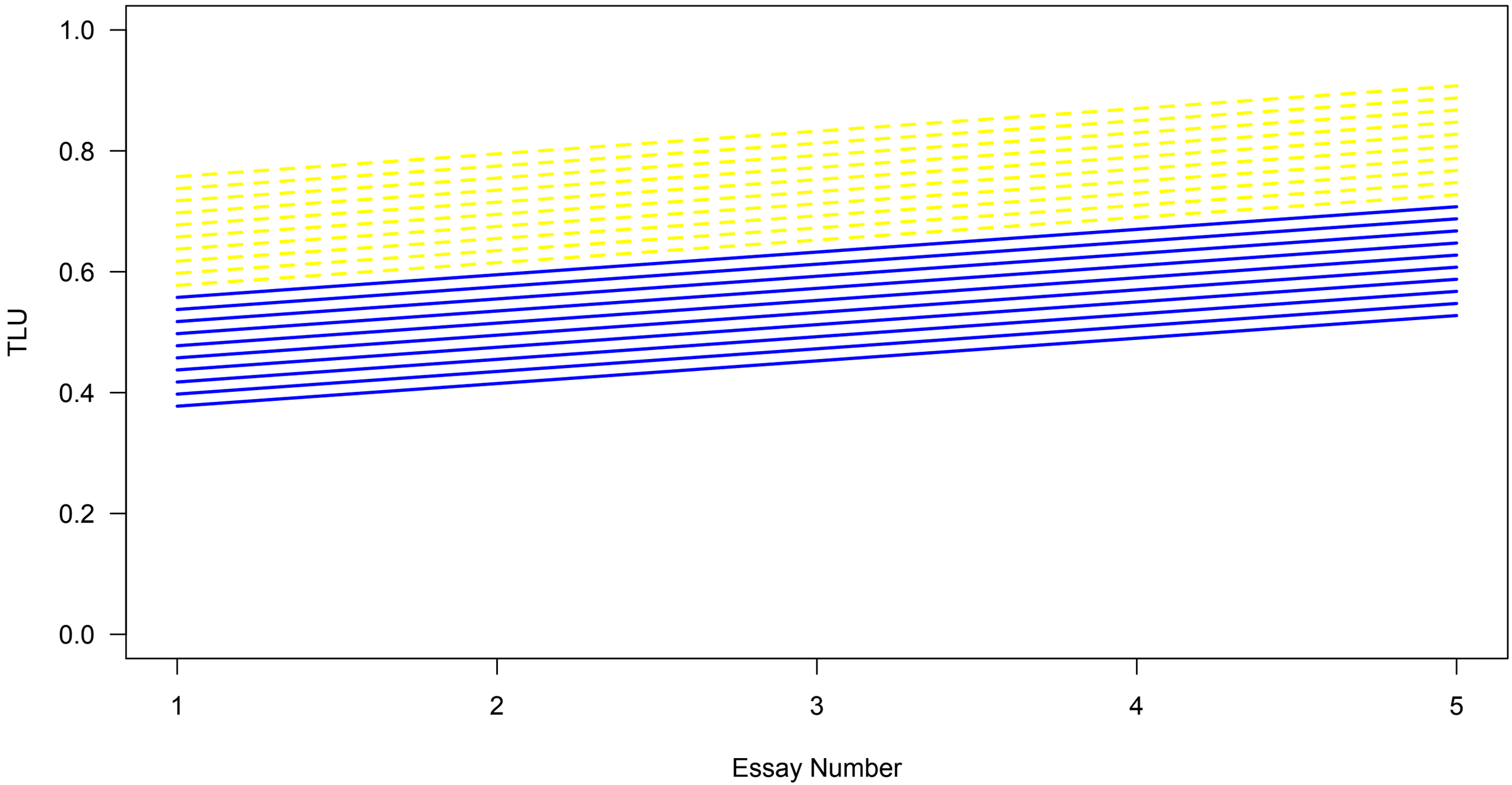

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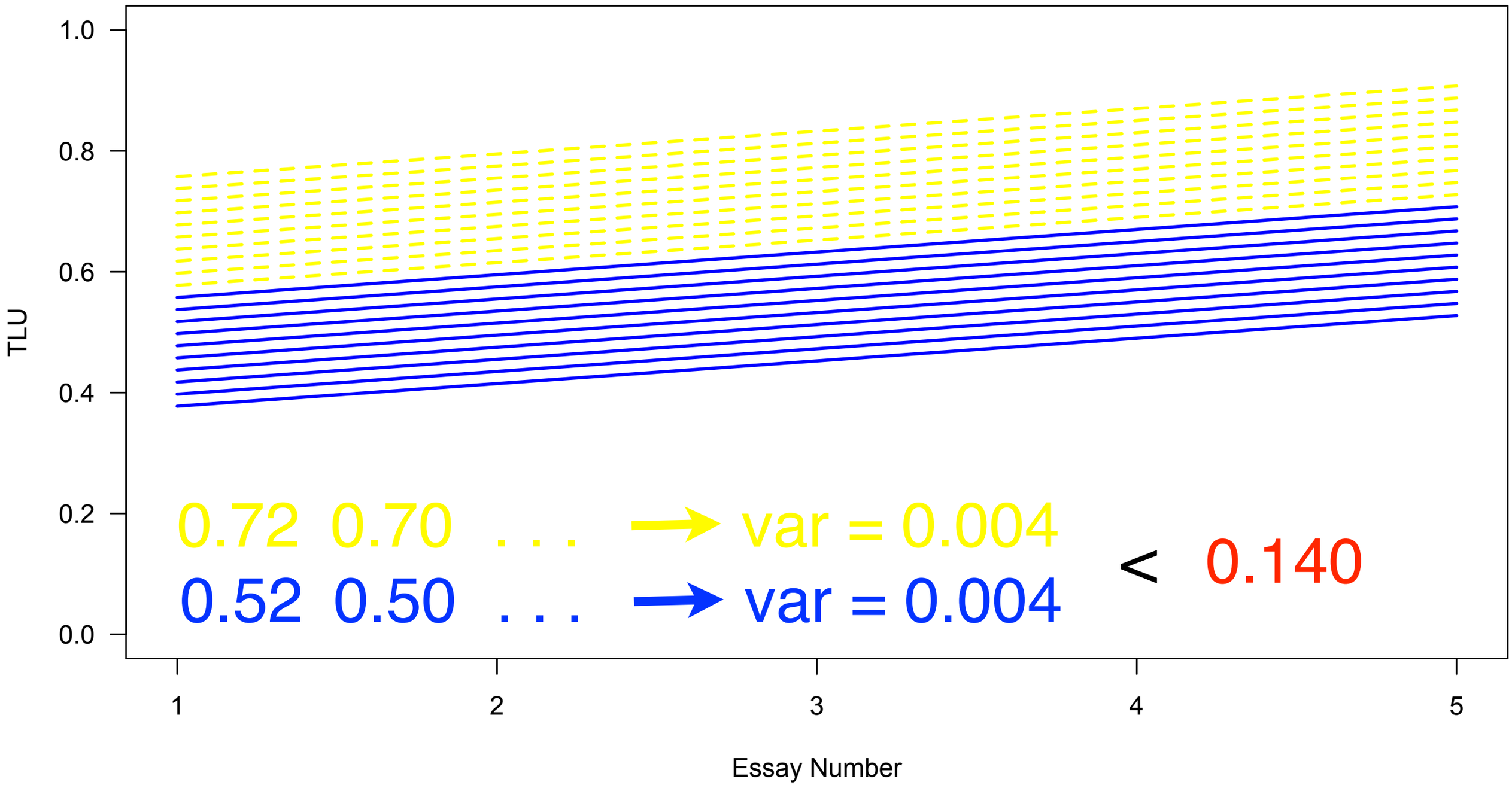

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Individual differences (IDs) in absolute accuracy

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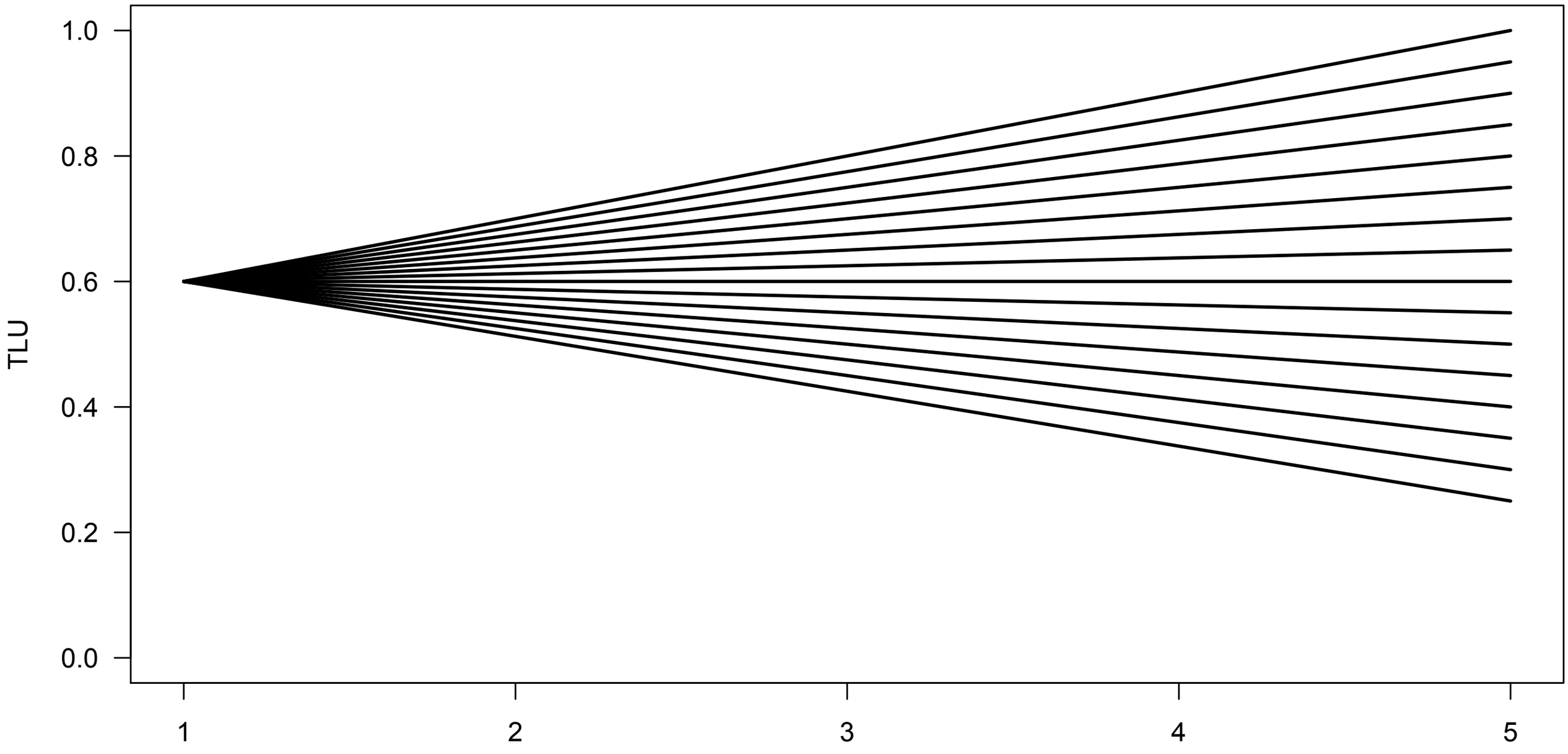
Individual differences (IDs) in absolute accuracy

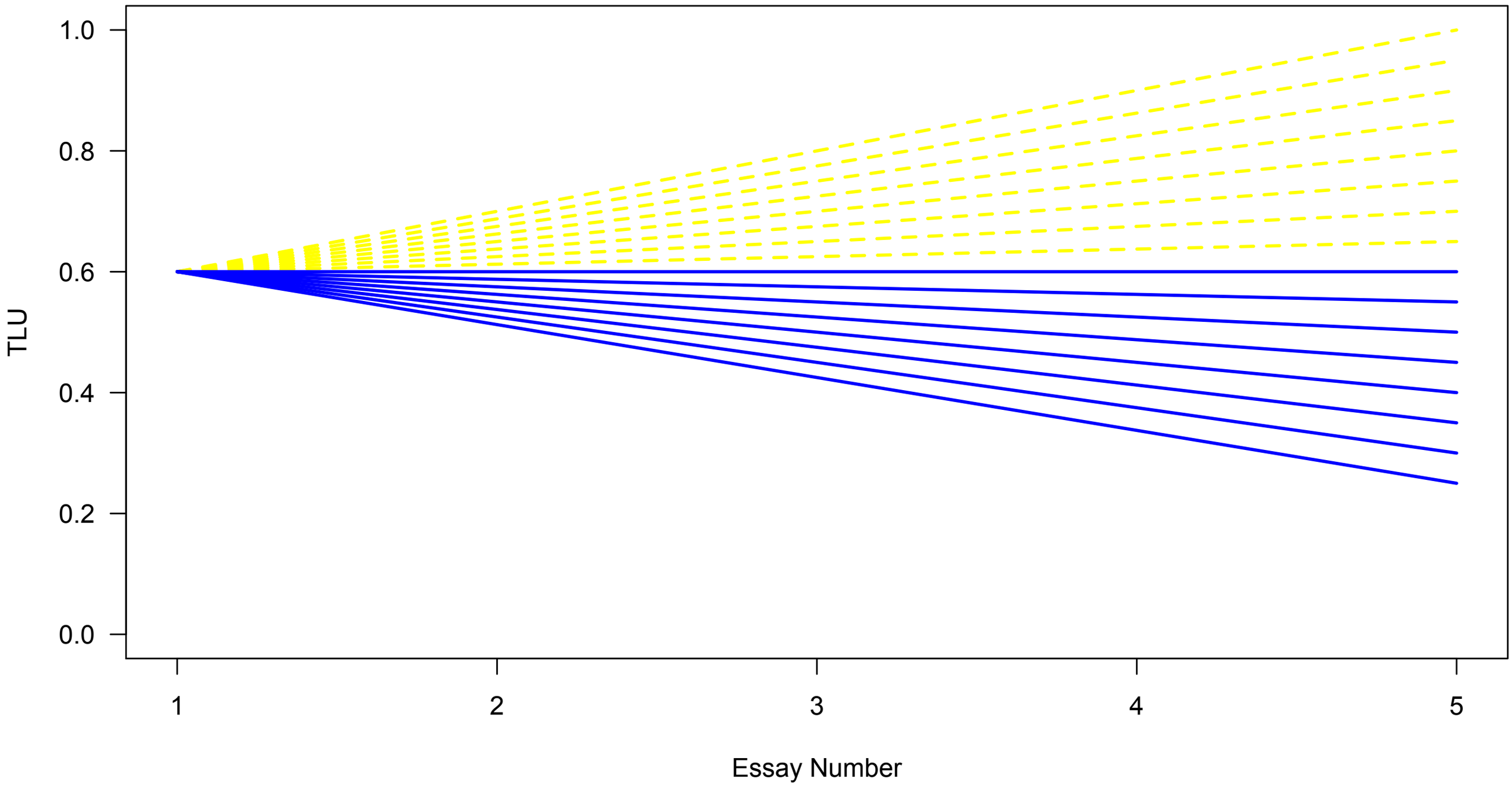
cf. EssayNum.Standardized in fixed-effects = 0.140

(1 SD of EssayNum ≈ 2/3 CEFR level)

Demonstration of Random-Slopes



Demonstration of Random-Slopes



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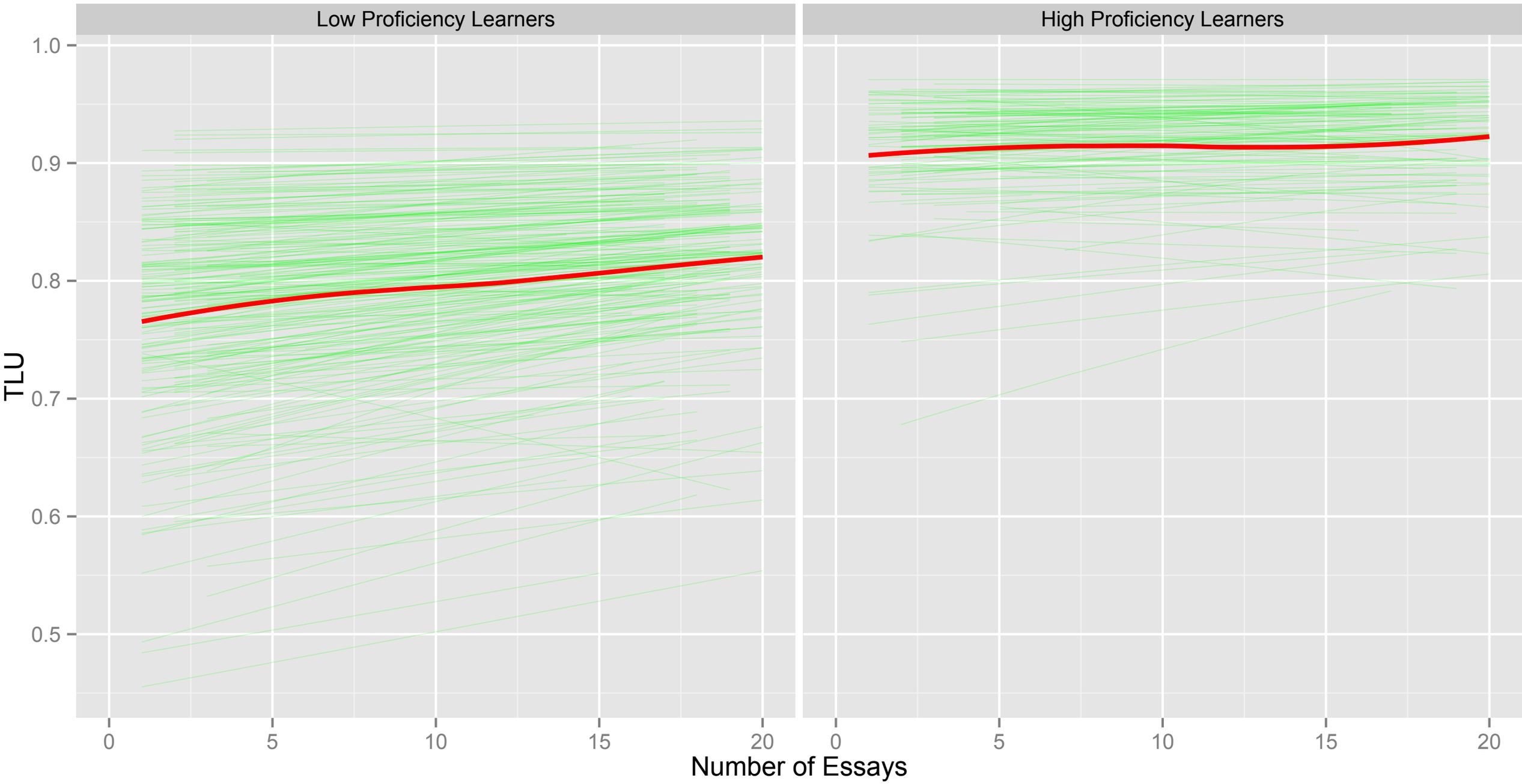
IDs in the rate of accuracy increase

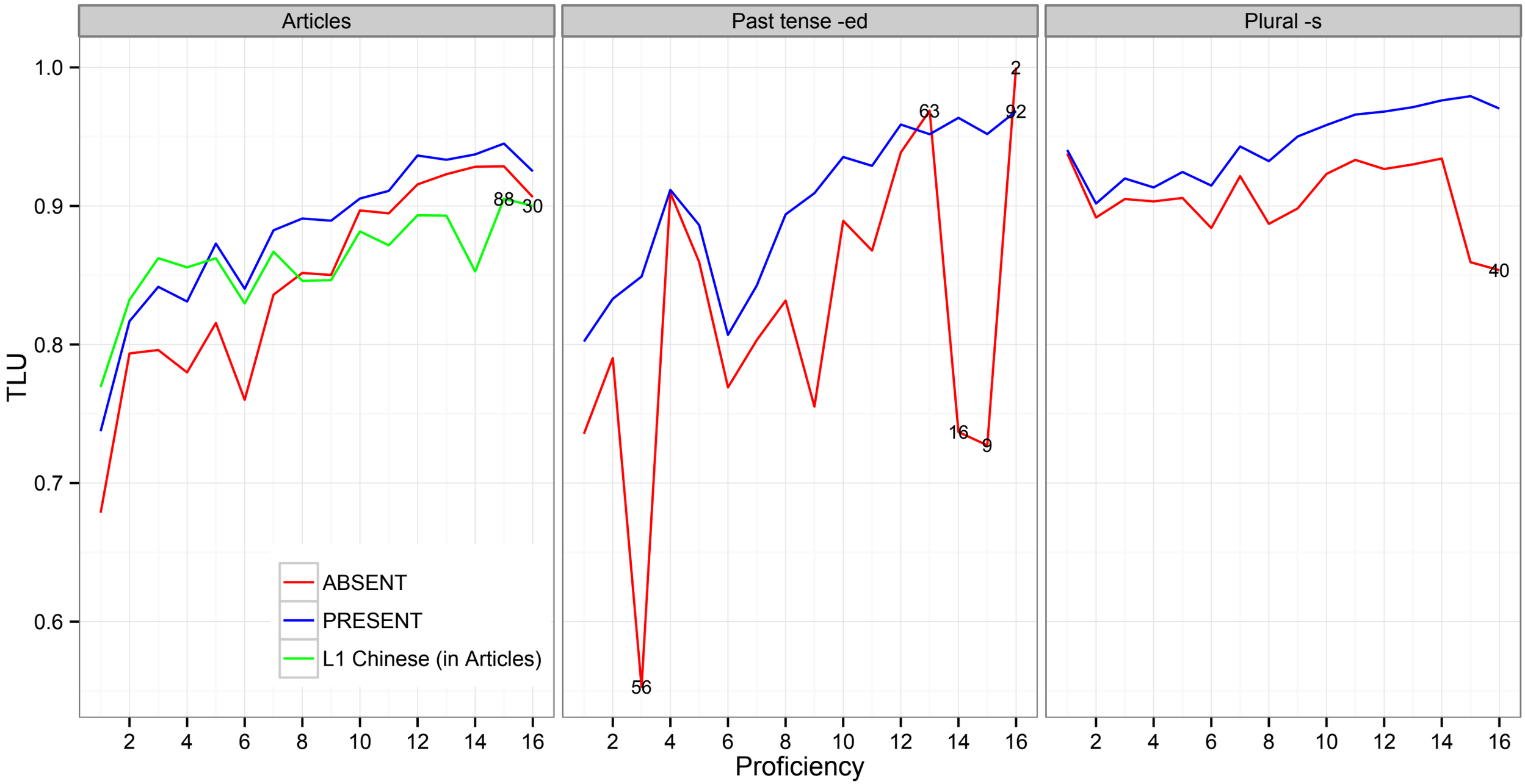
Findings Based on Mixed-Effects Modeling

- Large individual variation in
  - overall accuracy
  - accuracy difference between articles and the other morphemes, and
  - the rate of development
- Despite large individual differences, proficiency and morpheme explain the variation to a certain degree
  - Developmental shape is different depending on learners' overall proficiency and on the morpheme concerned
  - But no evidence for differing rate of development by L1

Fitted Values of Model 2 for Low- vs High-Proficiency Learners



Cross-Sectional View of the Development



Generalised Additive Model (GAM)

- The relationship between independent and dependent variables is estimated by a nonlinear function.
- GAMs are semi-parametric, allowing both parametric and nonparametric terms in one model.
- In the present study,
  - L1, morpheme, and their interaction were entered as parametric terms.
  - A tensor product spline for the interaction between the overall proficiency and the within-learner development was obtained for each L1-Morpheme pair.

Models Considered

- Similar to the mixed-effects models
- Model 1: Maximal model
- Model 2: Tests the effect of L1
- Model 3: Tests the effect of Proficiency
- Model 4: Tests the effect of Morpheme

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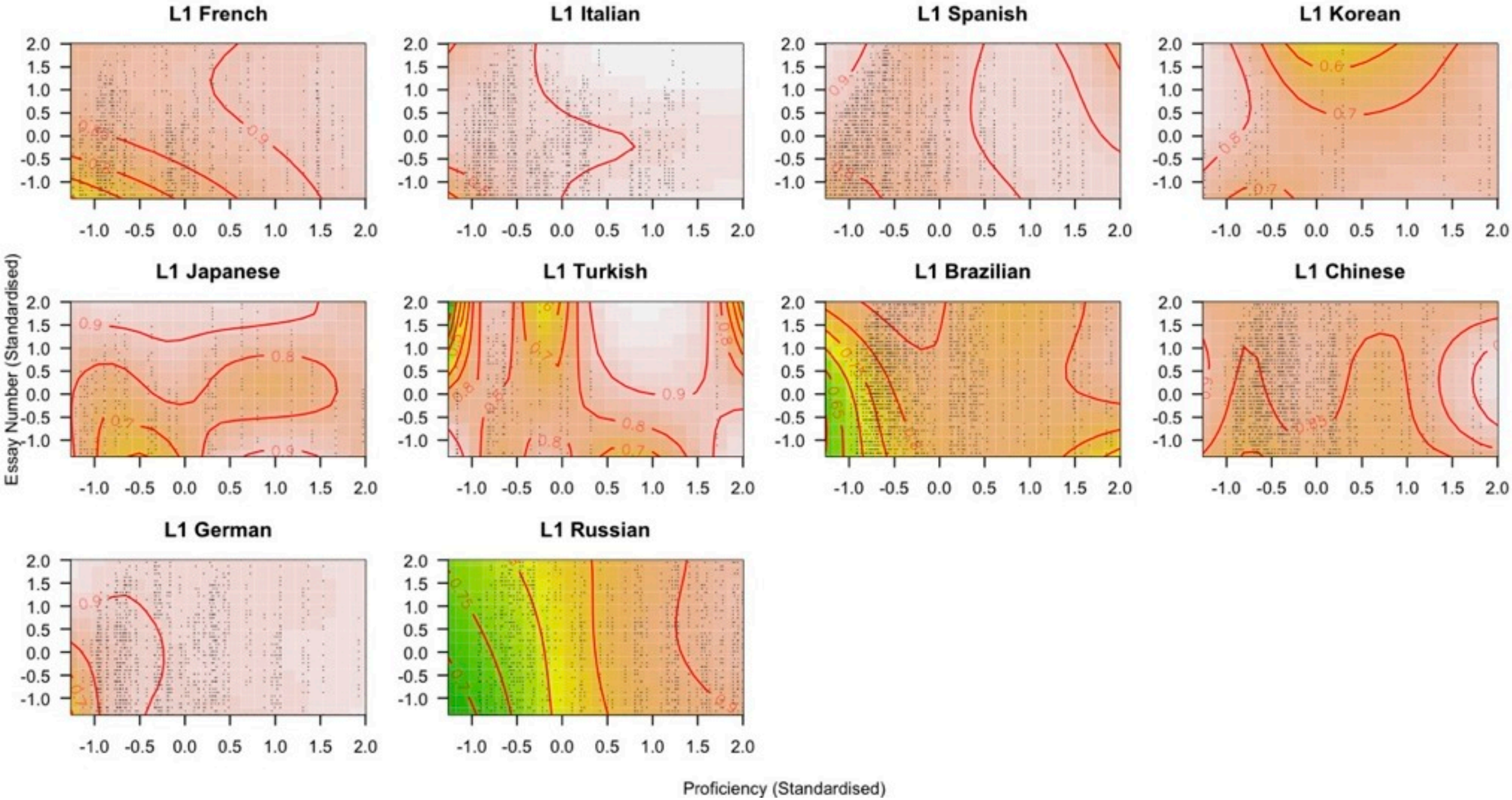
Article Development



Findings Based on the GAM

- Striking nonlinearity in morpheme accuracy development
- The nonlinear effects further interact with L1, proficiency, and morpheme, that is, the developmental patterns vary across learners' L1s, proficiency levels, and morphemes.
- When nonlinearity is taken into account, both L1 and proficiency affect the developmental patterns of accuracy.

Regression Summary

- We observe significant individual variation. However, the developmental patterns are not random.
- Proficiency systematically affects the developmental pattern
  - e.g., Ceiling effect
- L1 influence not clear
  - The mixed-effects analysis failed to show the significance of L1 influence

Interpretation

- Dynamic systems theory (DST; Verspoor, de Bot, & Lowie, 2011)
- variability
  - one's linguistic system = dynamic system
  - Dynamic systems are in complex interactions
  - ➡ constant change with chaotic variation
  - complete interconnectedness
- stability
  - attractor state

Conclusion

- Significant individual differences are present in L2 morpheme development.
- Systematicity is present at the same time.
- They are in line with DST.

References

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