

Applications of Online Learning Systems

Modeling Individual Differences in Error-Induced Quitting



IMPS 2024
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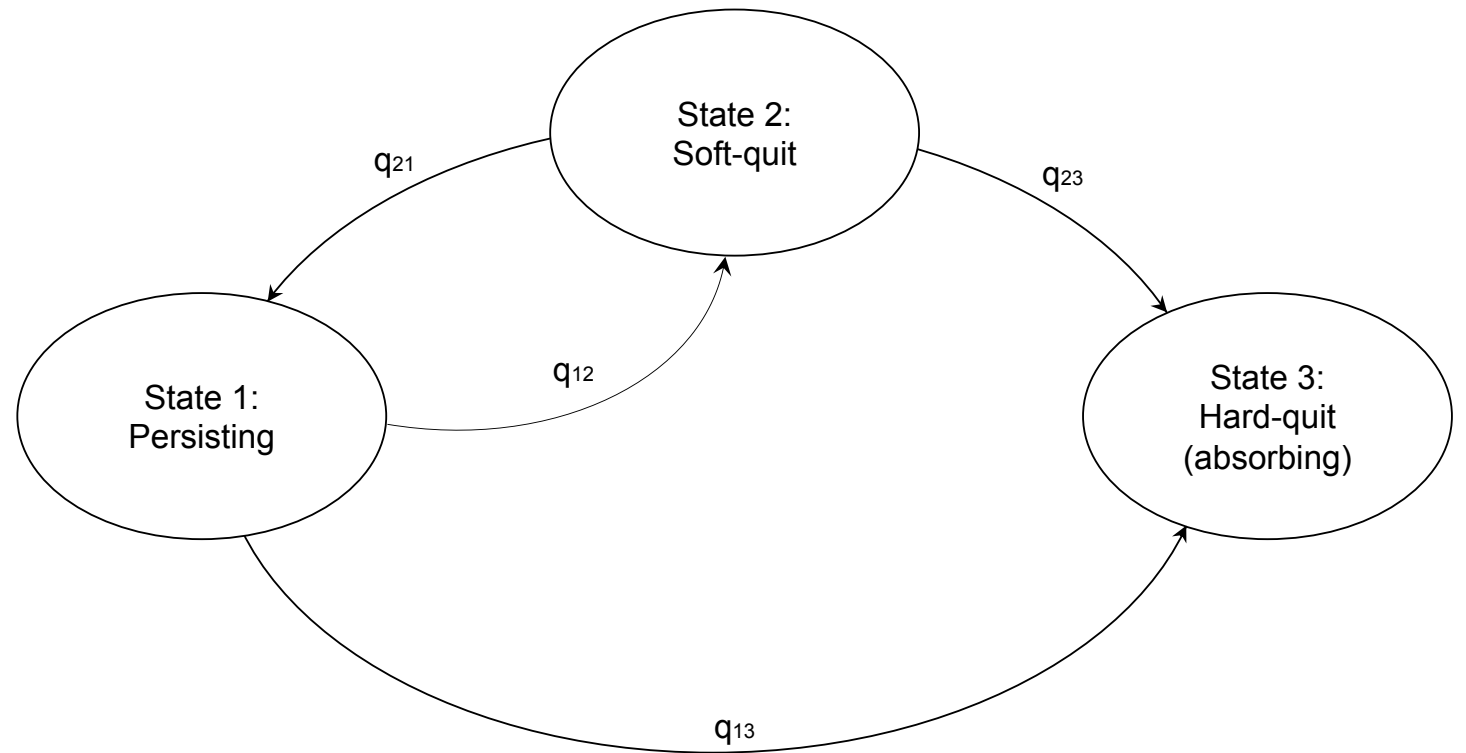
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Why do students quit learning?

- Engagement is crucial for learning
- Online disengagement and drop-out is common
- In Math Garden, ~30% of sessions are exited prematurely

Sequential errors predict quitting

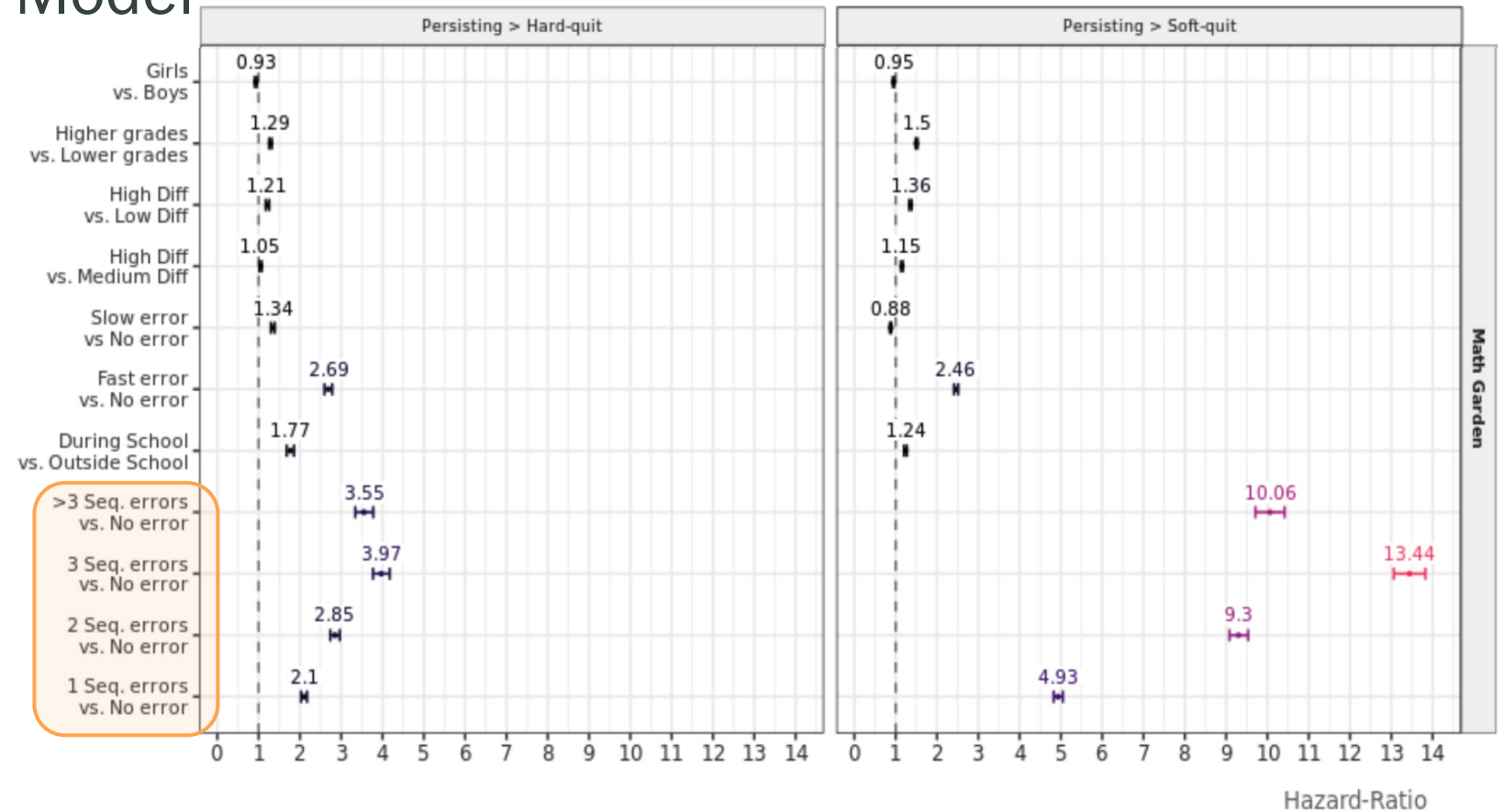
- Multi-State Survival Model



ten Broeke, N., Hofman, A. D., Kruis, J., de Mooij, S. M. M., & van der Maas, H. (2022) [preprint].

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Sequential errors predict quitting

- Sufficient motivation, grit, and self-regulation are important for successful engagement in learning (Skinner et al., 2020)
- These are traits that vary considerably across children (Hill et al., 2016; Miller et al., 2012)
- It is possible that sequential errors do not affect children equally.
- **RQ: Are there individual differences in the effect of sequential errors on quitting?**

Are there individual differences in the effect of sequential errors on quitting?

1. Zoom into quitting behavior by looking at variability in a large dataset for one domain (addition):
 - a) Estimate state transitions between persisting and quitting across individual-level variables
 - b) Look at error-induced quitting over time
 - c) Model the effect of sequential errors on quitting per individual

2. Examine the reliability of these findings:
 - a) By validating them in a 50% testing dataset
 - b) By correlating them with a different domain (subtraction)

Data

- Three years of responses (> 25 million) to addition items (2021-2023)
- Exploratory analyses on training data (50%; $n = 107000$)
- Confirmatory analyses on a validation set (50%).



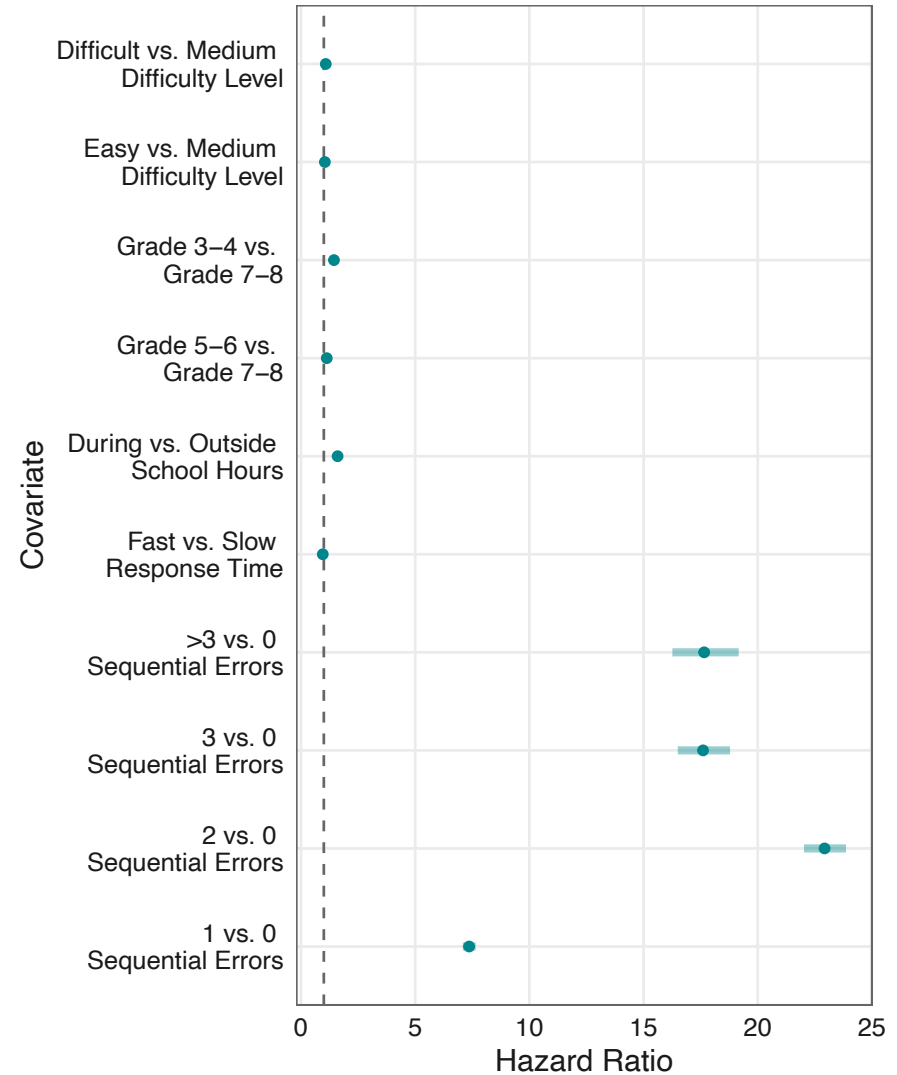
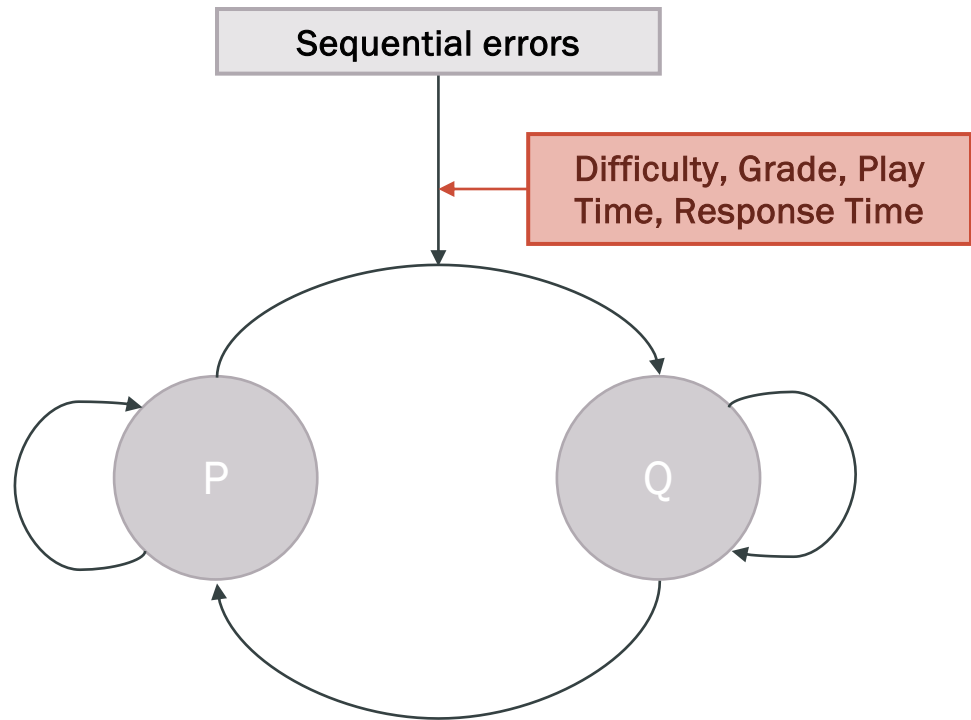
Prowise

Are there individual differences in the effect of sequential errors on quitting?

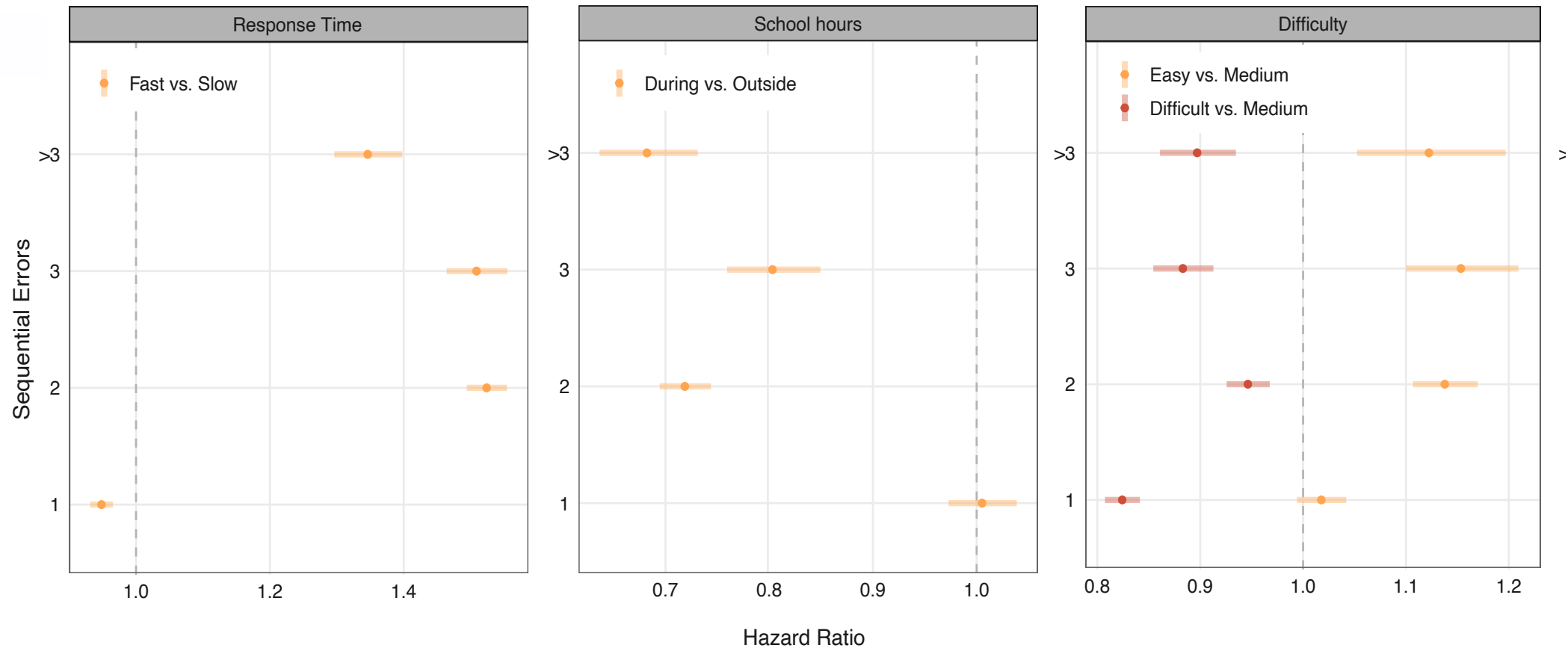
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2-State Markov Model



The effect of sequential errors on quitting differs across response time, play time, and difficulty level

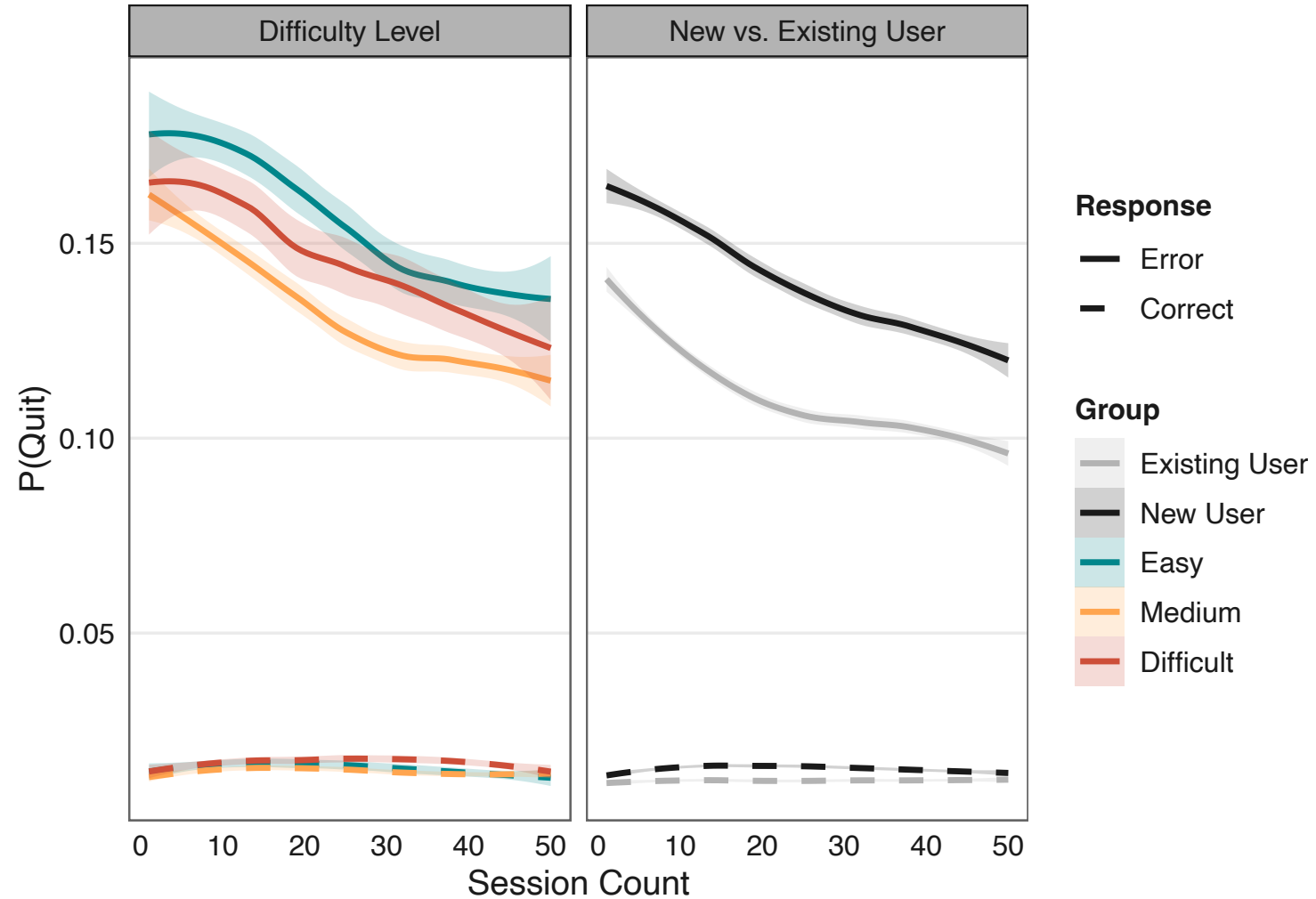


Are there individual differences in the effect of sequential errors on quitting?

1. Zoom into quitting behavior by looking at variability in a large dataset for one domain (addition):
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The effect of sequential errors on quitting differs across time

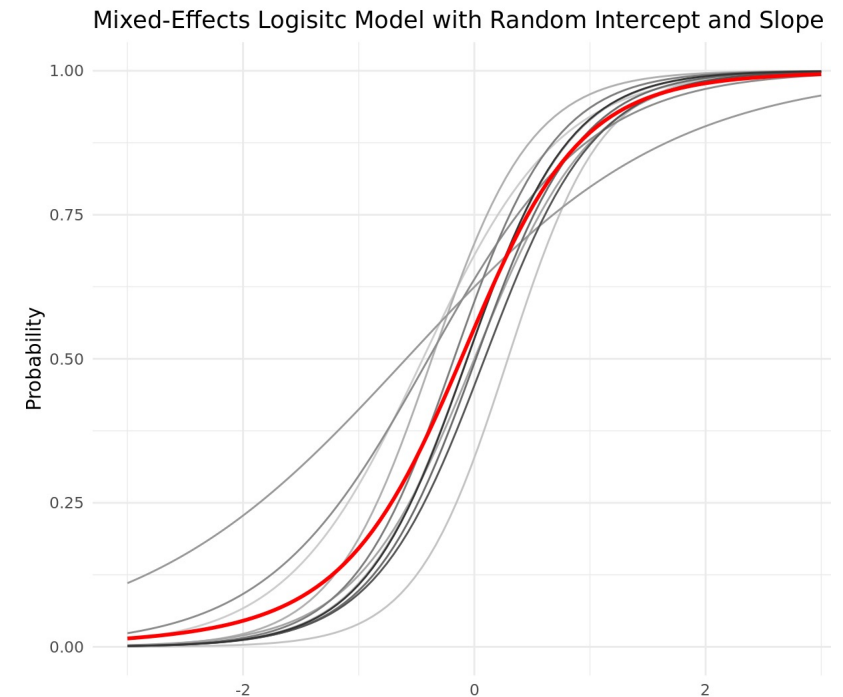


Are there individual differences in the effect of sequential errors on quitting?

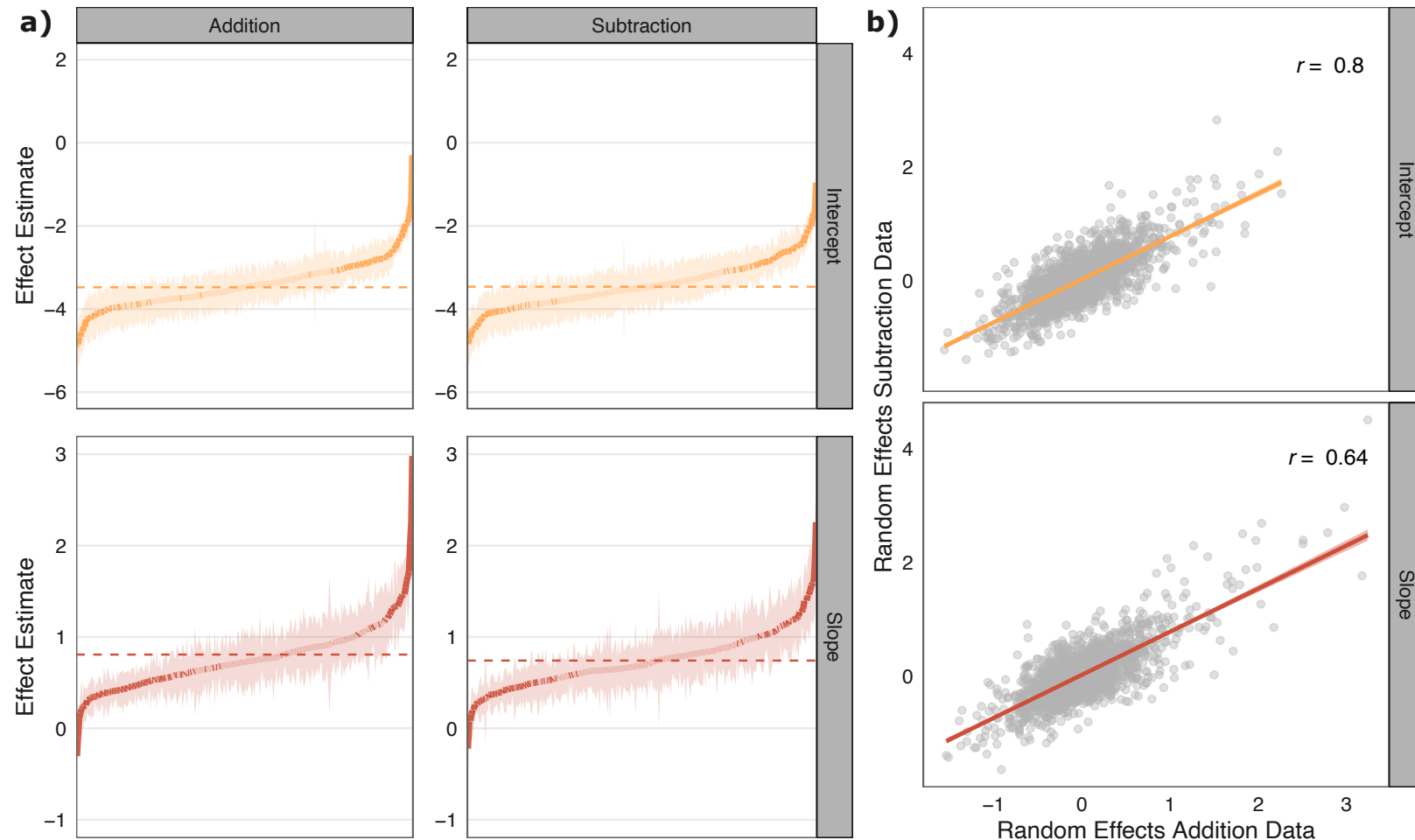
1. Zoom into quitting behavior by looking at variability in a large dataset for one domain (addition):
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 - c) **Model the effect of sequential errors on quitting per individual**
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Mixed effects logistic regression

- Probability to quit predicted by sequential errors
- Random intercept and slope with covariates (rating and grade)
 - Random intercept: allowing baseline quit rates to vary across users
 - Random slope: allowing the effect of sequential errors on quitting to vary across users
 - Controlling for ability (rating) and age (grade)
- Sequential error variable is continuous rather than categorical.
- Addition ($n = 3998$) and subtraction ($n = 1765$) domains



There is wide individual variability in error-induced quitting across addition and subtraction



Three strikes and you're out?



Three strikes and you're out? **Not always.**

- There are **considerable individual differences** in students' vulnerability to errors.
- These effects are **stable** across 2 math games.
 - Individual effects of errors in addition can be used to predict effects in subtraction.
- Implications for **tailored interventions**.
 - One size does not fit all!
- **Challenges & Future directions**
 - Data selection
 - Mechanisms
 - A/B testing
 - Error intervention



Thank you!

Contact: a.m.johansson2@uva.nl



Preprint!



Thank you!

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References

Ten Broeke, N., Hofman, A. D., Kruis, J., de Mooij, S. M. M., & van der Maas, H. (2022). Predicting and Reducing Quitting in Online Learning [Preprint]. *Open Science Framework*.

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Hill, K. E., Samuel, D. B., & Foti, D. (2016). Contextualizing individual differences in error monitoring: Links with impulsivity, negative affect, and conscientiousness: Personality and error processing. *Psychophysiology*, 53(8), 1143–1153. <https://doi.org/10.1111/psyp.12671>

Miller, A. E., Watson, J. M., & Strayer, D. L. (2012). Individual differences in working memory capacity predict action monitoring and the error-related negativity. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 38(3), 757–763. <https://doi.org/10.1037/a0026595>

Skinner, E. A., Graham, J. P., Brule, H., Rickert, N., & Kindermann, T. A. (2020). “I get knocked down but I get up again”: Integrative frameworks for studying the development of motivational resilience in school. *International Journal of Behavioral Development*, 44(4), 290–300.

<https://doi.org/10.1177/0165025420924122>



3.2 Supplementary Table 5: Fixed effects on the addition data.

Supplementary Table 5. GLMER Model Statistics: Fixed effects on the addition data.

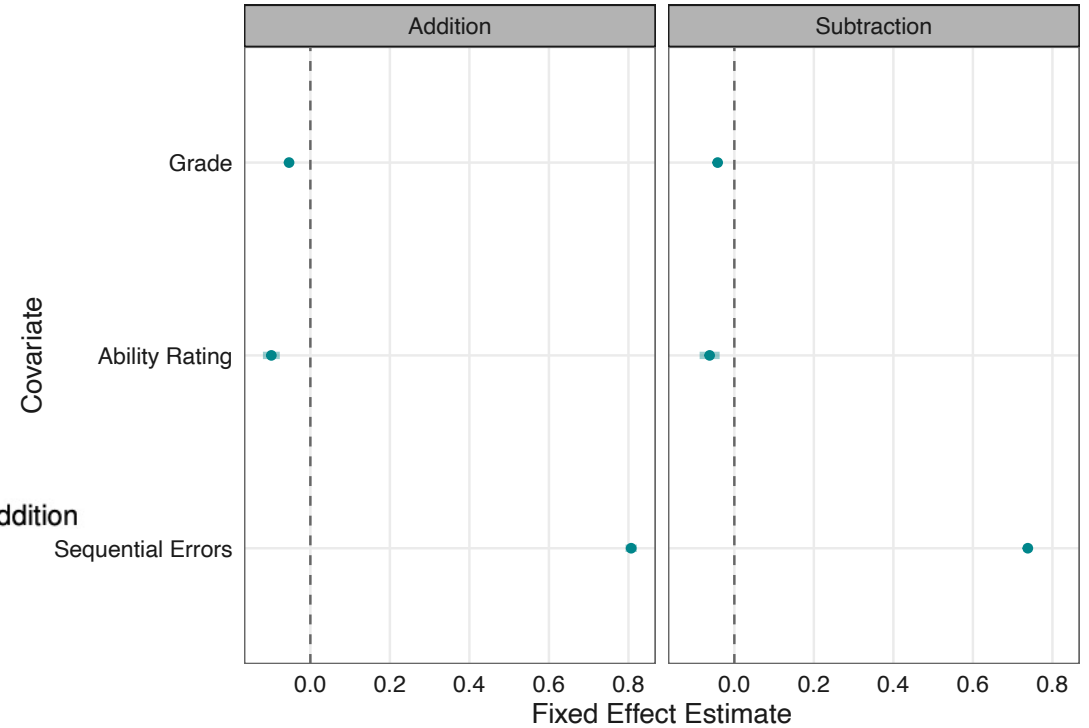
	Training Data				Testing Data			
	Estimate	SE	z value	p value	Estimate	SE	z value	p value
(Intercept)	-3.48	0.02	-152.11	<0.001	-3.57	0.02	-149.97	<0.001
Sequential Error	0.81	0.01	119.57	<0.001	0.81	0.01	125.46	<0.001
Rating	-0.10	0.01	-8.83	<0.001	-0.09	0.01	-8.09	<0.001
Grade	-0.05	0.00	-12.07	<0.001	-0.03	0.00	-7.30	<0.001

Note. SE = Standard Error.

3.3 Supplementary Table 6: Random effects on the addition data.

Supplementary Table 6. GLMER Model Statistics: Variance Estimates of Random Effects in the Addition Data

	Training Data		Testing Data	
	Estimate	Std. Deviation	Estimate	Std. Deviation
(Intercept)	0.39	0.62	0.41	0.64
Sequential Error	0.14	0.38	0.13	0.36



3.4 Supplementary Table 7: Correlation between fixed effects.

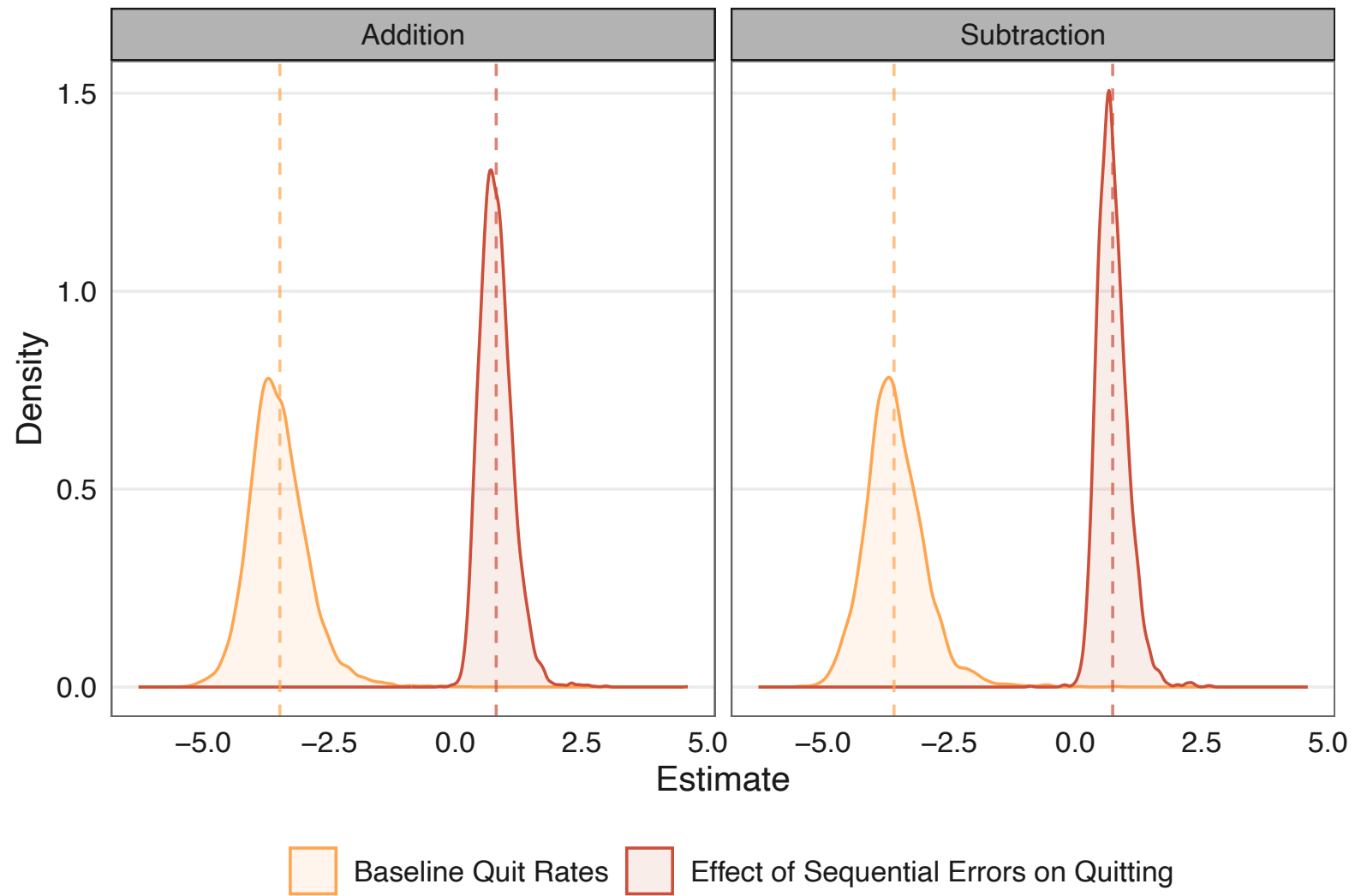
Supplementary Table 7. GLMER Model Statistics: Correlation between fixed effects

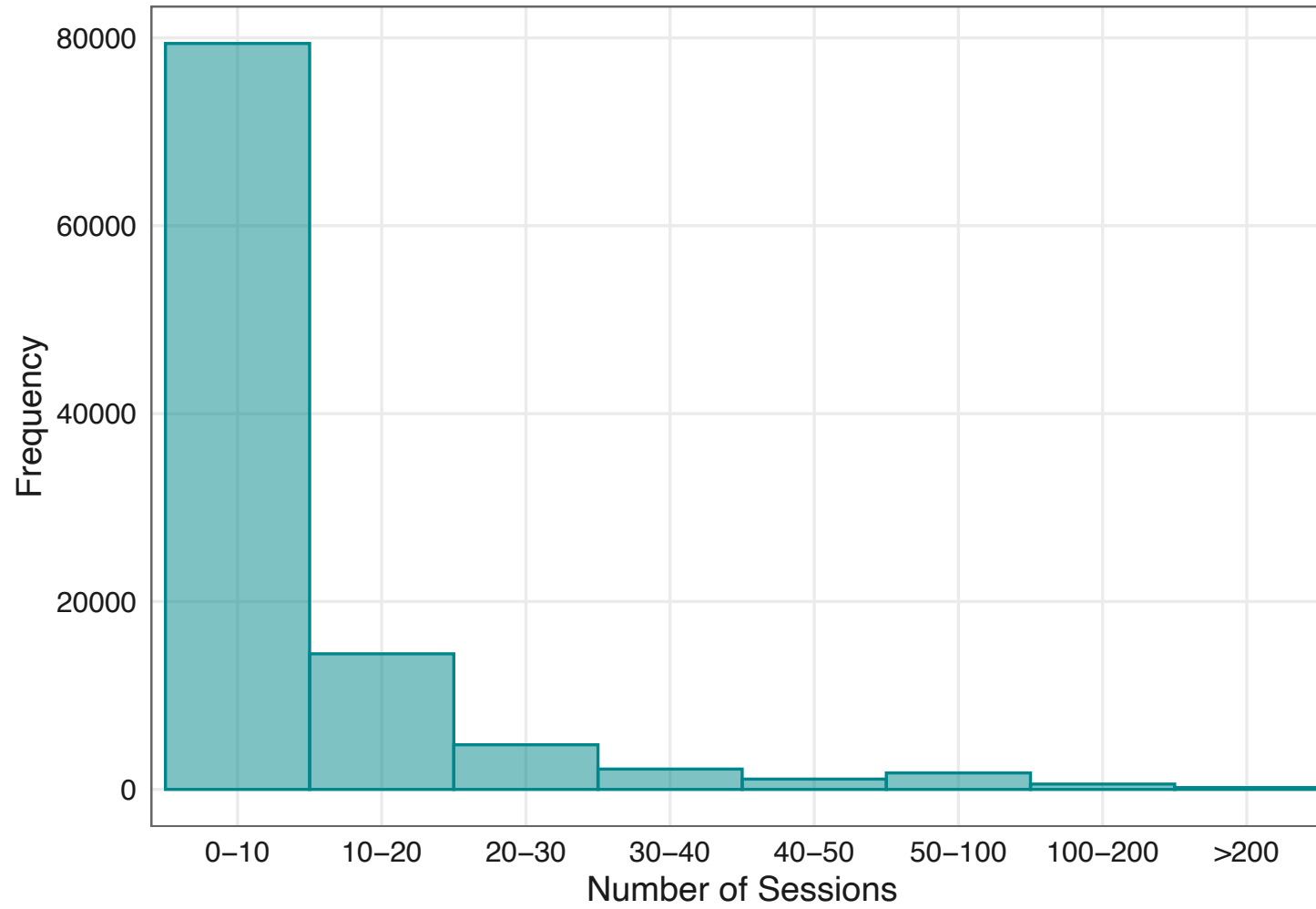
	Training Data				Testing Data			
	1.	2.	3.	4.	1.	2.	3.	4.
1. (Intercept)	1.000	-0.073	0.281	-0.886	1.000	-0.095	0.263	-0.891
2. Sequential Errors	-0.073	1.000	0.007	-0.018	-0.095	1.000	-0.005	0.006
3. User Rating	0.281	0.007	1.000	-0.286	0.263	-0.005	1.000	-0.269
4. Grade	-0.886	-0.018	-0.286	1.000	-0.891	0.006	-0.269	1.000

3.5 Supplementary Table 8: Correlation between random effects.

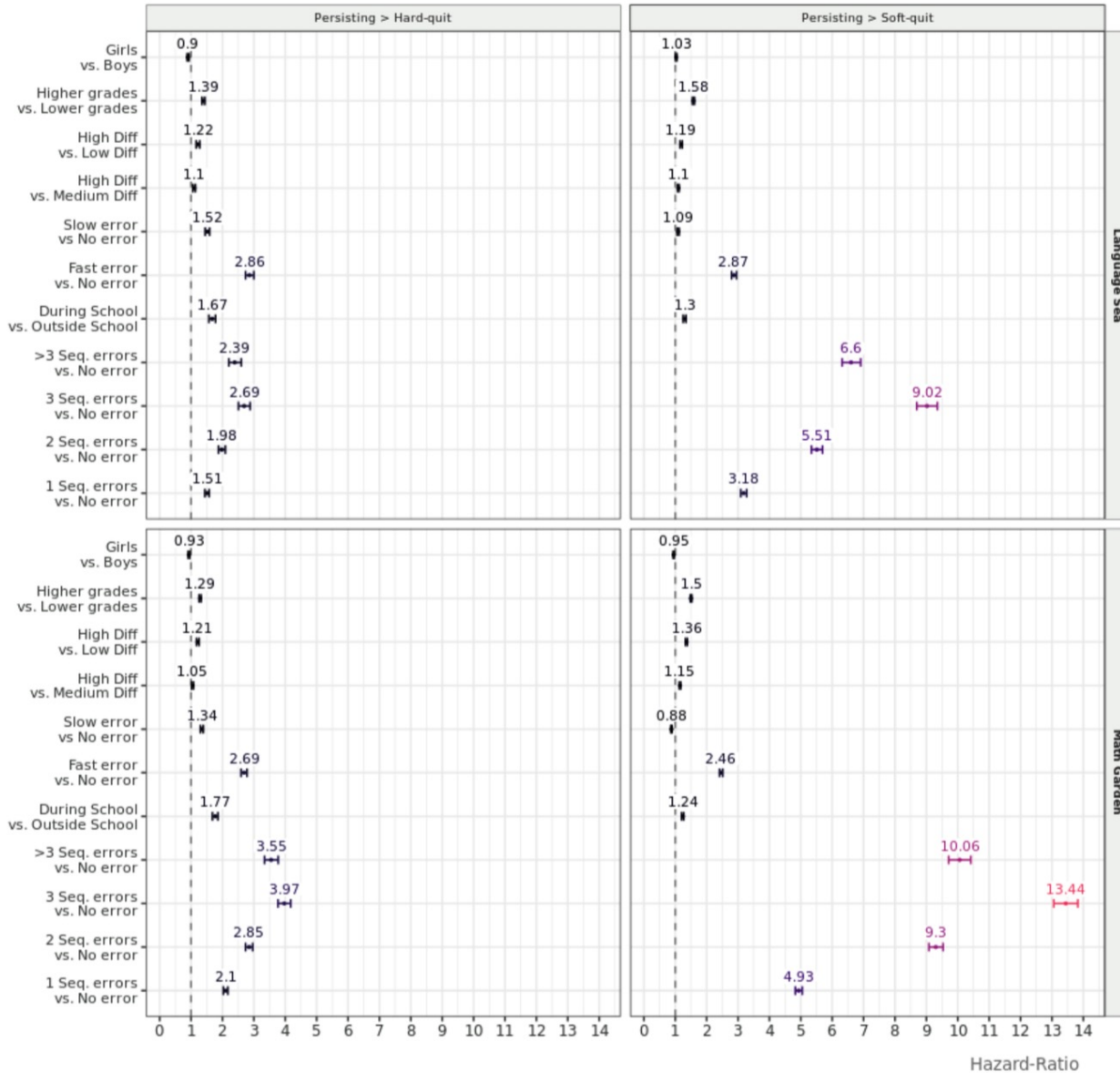
Supplementary Table 8. GLMER Model Statistics: Correlation between random effects.

Dataset	Variance-Covariance	Std. Correlation	<i>p</i> value
Training	-0.02	-0.10	<0.001
Testing	-0.02	-0.10	<0.001





2021



2023

