



A Benchmark Dataset for Evaluating Sentence Processing Models in German

Sentence Processing Workshop in Golm

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1 Introduction

Benchmark data are essential for theory building and model testing.

In sentence processing, there is an **urgent need** for datasets covering multiple experimental designs in a single large participant sample.

One such dataset was created by Huang et al. (2024), covering several syntactic ambiguity phenomena in English (SAP Benchmark).



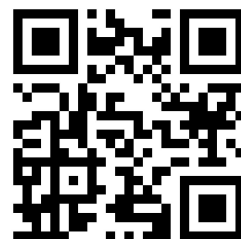
1 Introduction



Here, I present **ongoing work** on the creation of a **new benchmark dataset** for sentence processing in **German**.

It includes both **self-paced reading** and **eye-tracking** data.

2 The German Benchmark Dataset



osf.io/wpra9

GPSD (2×2): Garden Paths From Subject-vs.-Direct-Object Ambiguity
Ambiguous/Unambiguous × S-O/O-S — closely replicating Meng & Bader (2000a)

GPSI (2×2): Garden Paths From Subject-vs.-Indirect-Object Ambiguity
Ambiguous/Unambiguous × Active/Passive — loosely replicating Meng & Bader (2000b)

GPCA (2×2): Garden Paths From Coordination Ambiguity
NP-/VP-Coordination × AP-/PP-Modifier — closely replicating Konieczny et al. (2000)

GPMI (2×2): Garden Paths From Modifier-vs.-Indirect-Object Ambiguity
Modifier/No-Modifier × Ambiguous/Unambiguous — closely replicating van Kampen (2001)

2 The German Benchmark Dataset



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AGAT (2×2): Agreement Attraction in Grammatical Sentences

Singular-/Plural-Controller × Match/Mismatch — closely replicating Häussler (2009)

LOCO (2×2): Local Coherence

Coherent/Incoherent × Intervener/No-Intervener — closely replicating Paape & Vasishth (2016)

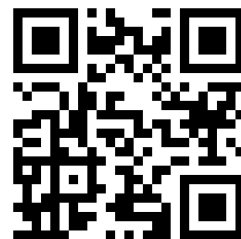
SBIN (2×2): Similarity-Based Interference

Subject-Cue [Yes/No] × Animacy-Cue [Yes/No] — closely replicating Schoknecht et al. (2025)

RCSO (2×2): Subject vs. Object Relative Clauses

Subject/Object × Double-/Single-Embedding — German adaptation of Hsiao & Gibson (2003)

2 The German Benchmark Dataset



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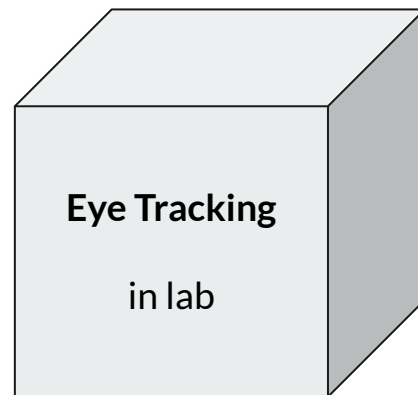
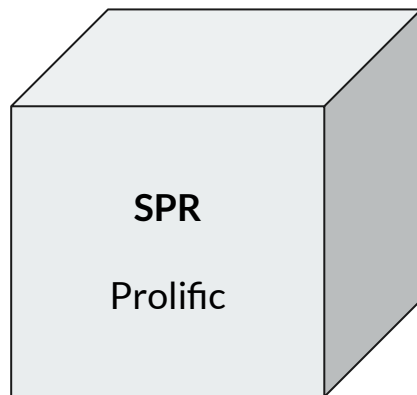
SYAA (3×1): Syntax-Based Attachment Ambiguity

High-/Low-/Ambiguous-Attachment — closely replicating Logačev (2023)

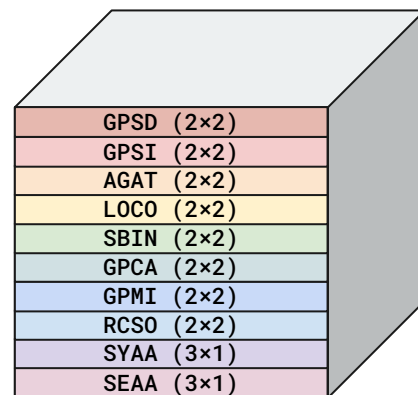
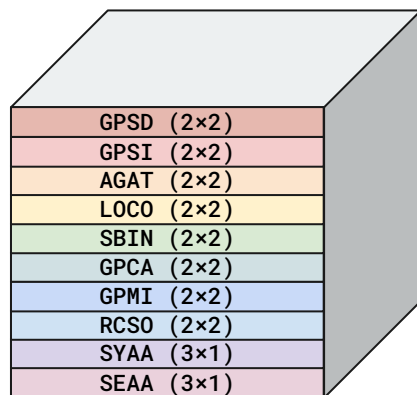
SEAA (3×1): Semantics-Based Attachment Ambiguity

High-/Low-/Ambiguous-Attachment — German adaptation of Traxler et al. (2023)

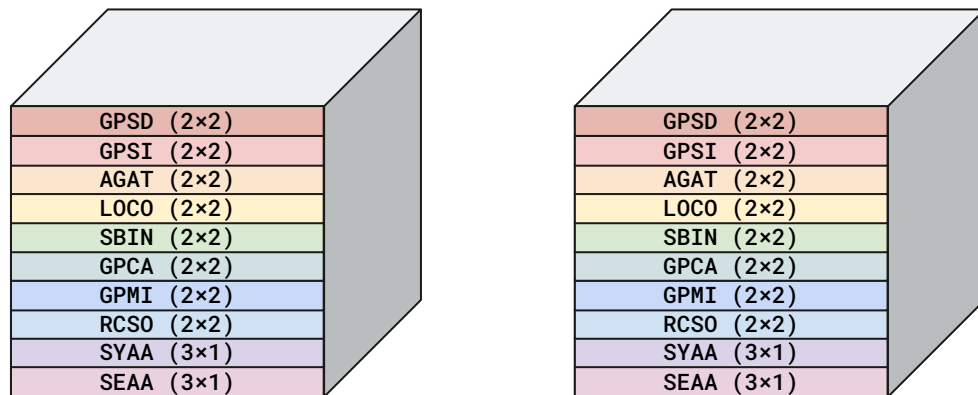
2 The German Benchmark Dataset



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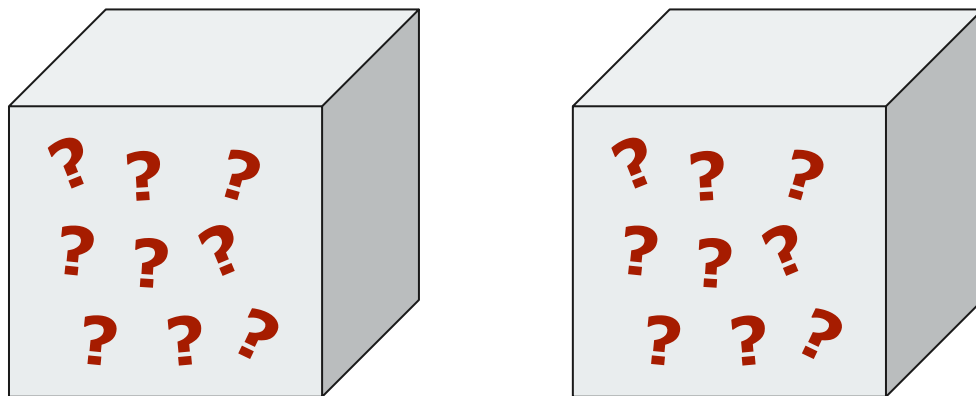
2 The German Benchmark Dataset



Three trials per condition per participant in a Latin square design

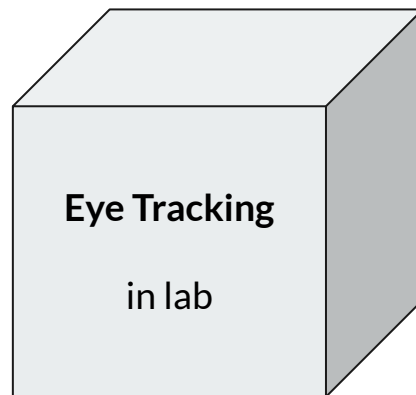
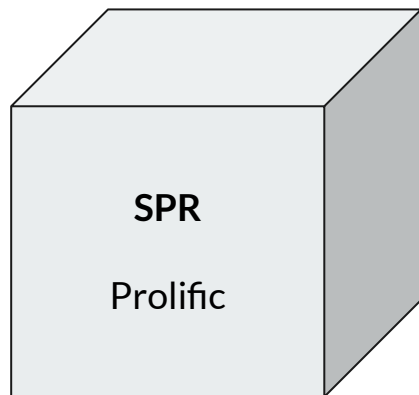
Overall trials per participant: **114** [= $8 \times 3 \times (2 \times 2) + 2 \times 3 \times (3 \times 1)$]

2 The German Benchmark Dataset



Every trial is followed by a **comprehension question** with two response options, targeting the key syntactic dependency.

3 Data Collection Status and Goal

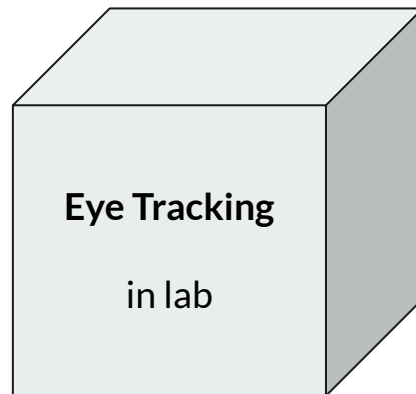
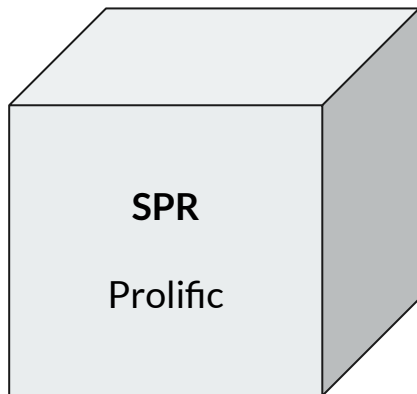


Already collected as of April 25, 2025:

$N = 659$

$N = 119$

3 Data Collection Status and Goal



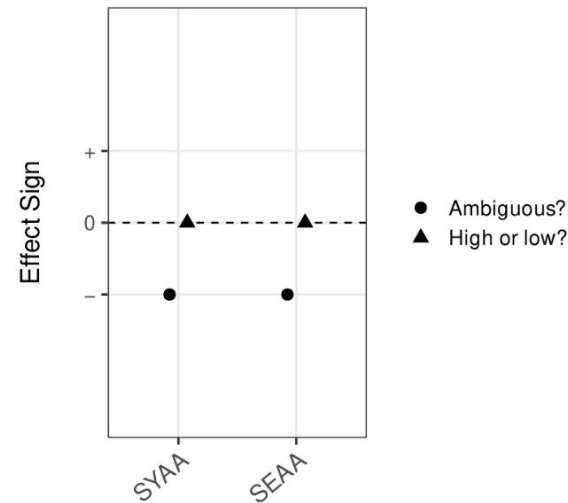
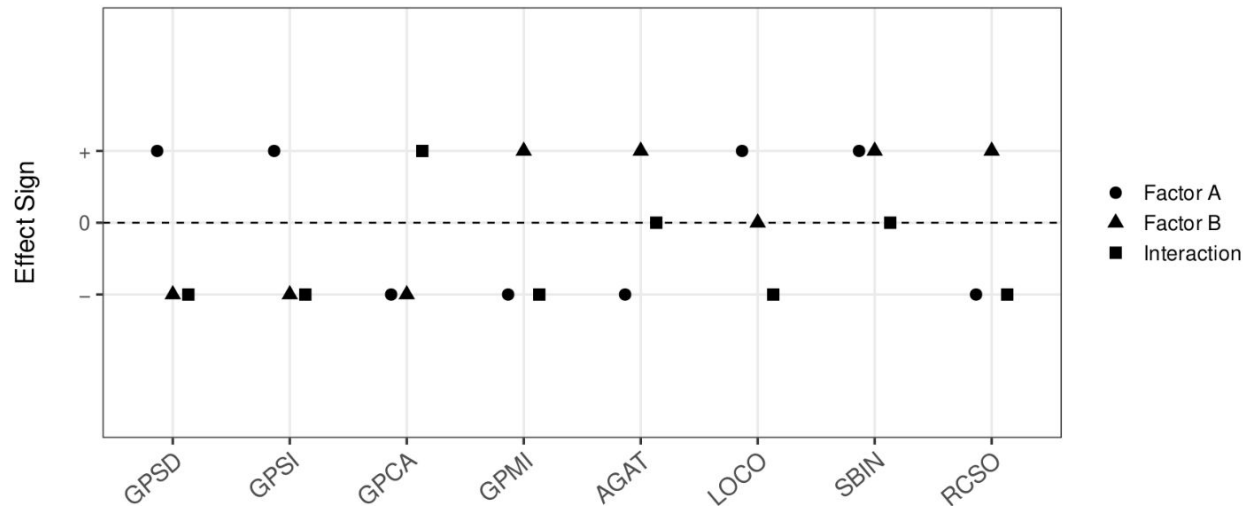
Goal:

$N = 1,100$

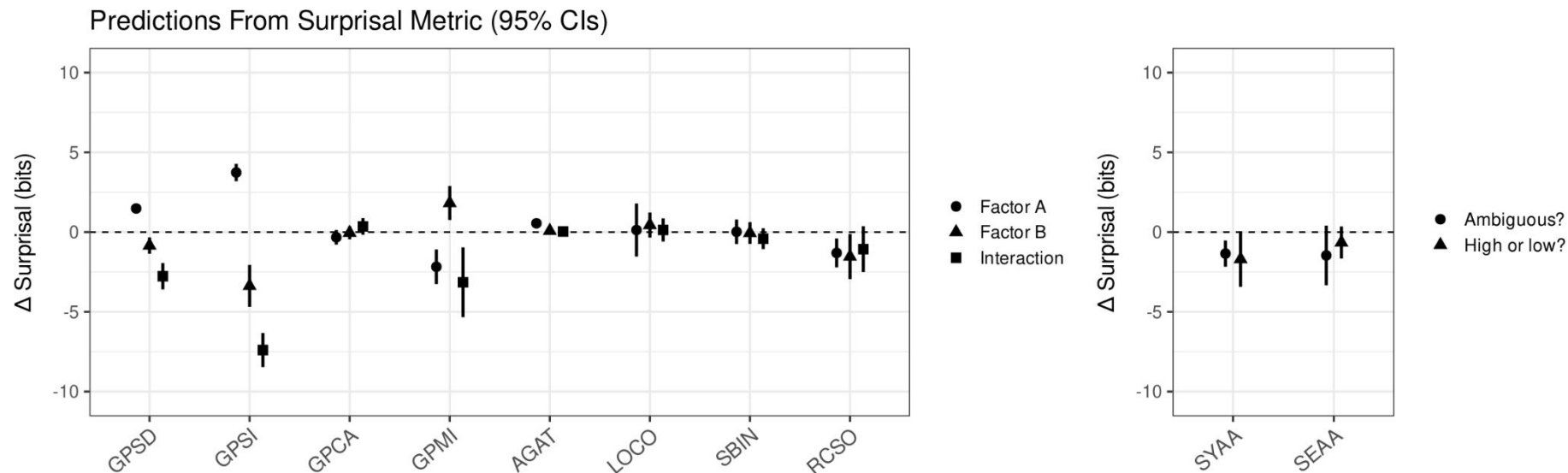
**Stop when *all* effect Crls on
TFTs range $\pm 50\text{ms}$ or less.**

4 Predictions and Observed Effects

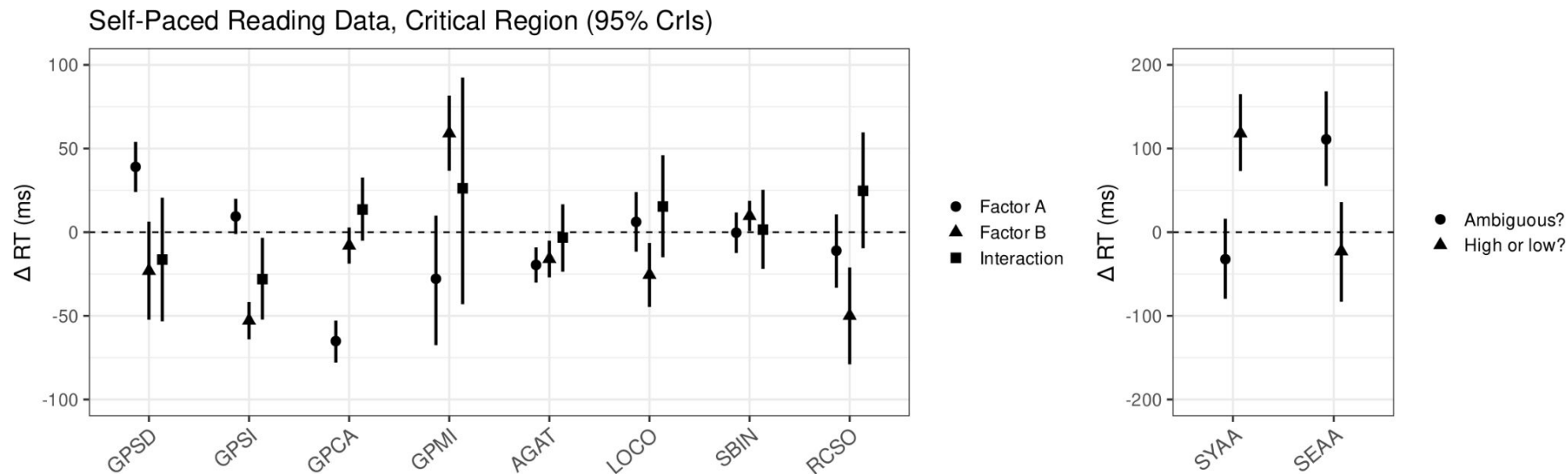
Predictions From Psycholinguistic Theory (Qualitative)



4 Predictions and Observed Effects

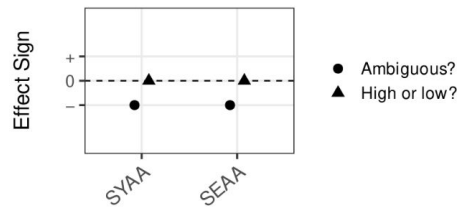
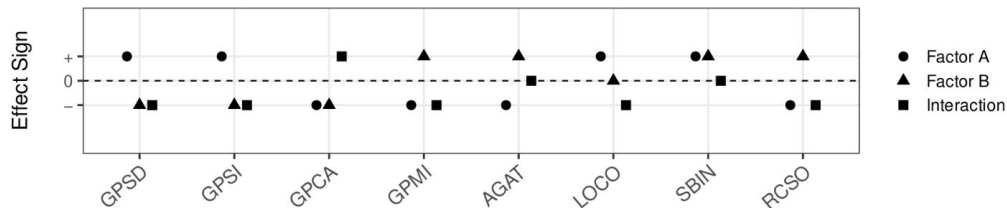


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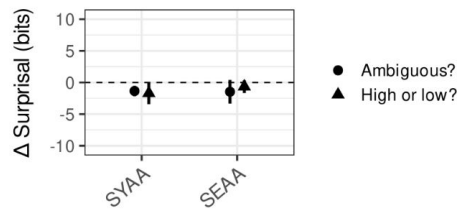
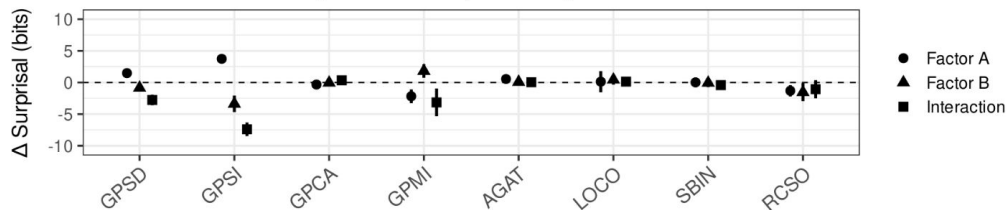


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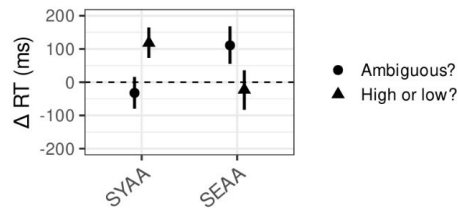
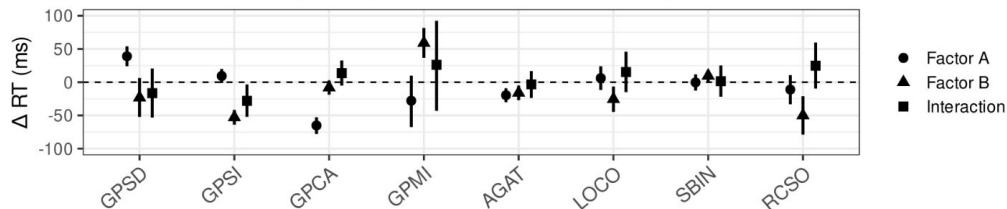
Predictions From Psycholinguistic Theory (Qualitative)



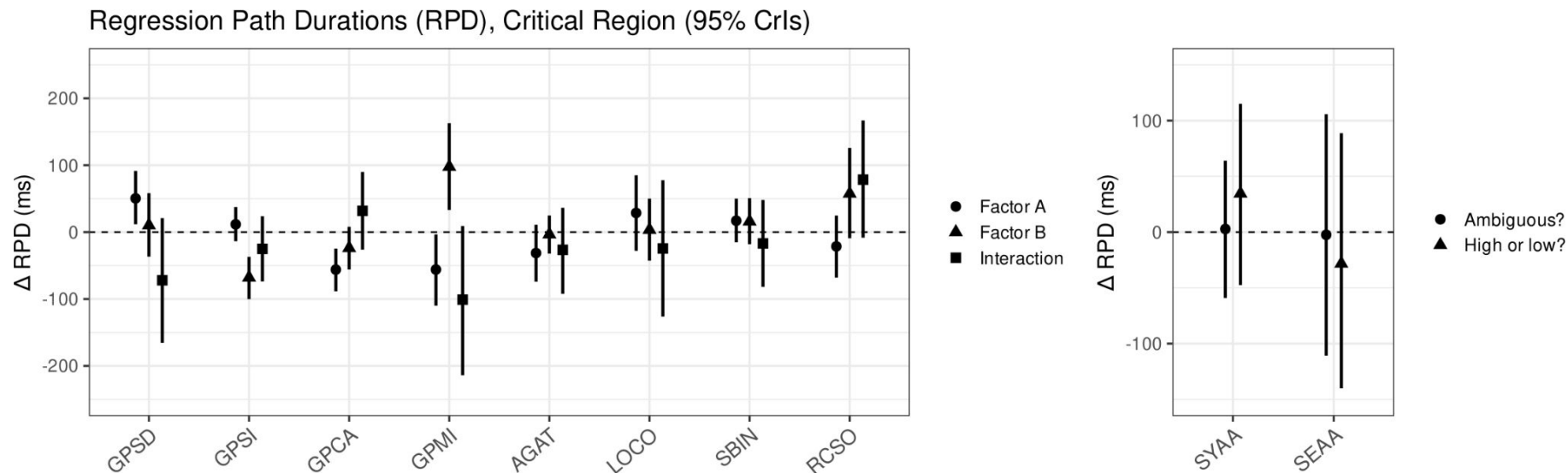
Predictions From Surprisal Metric (95% CIs)



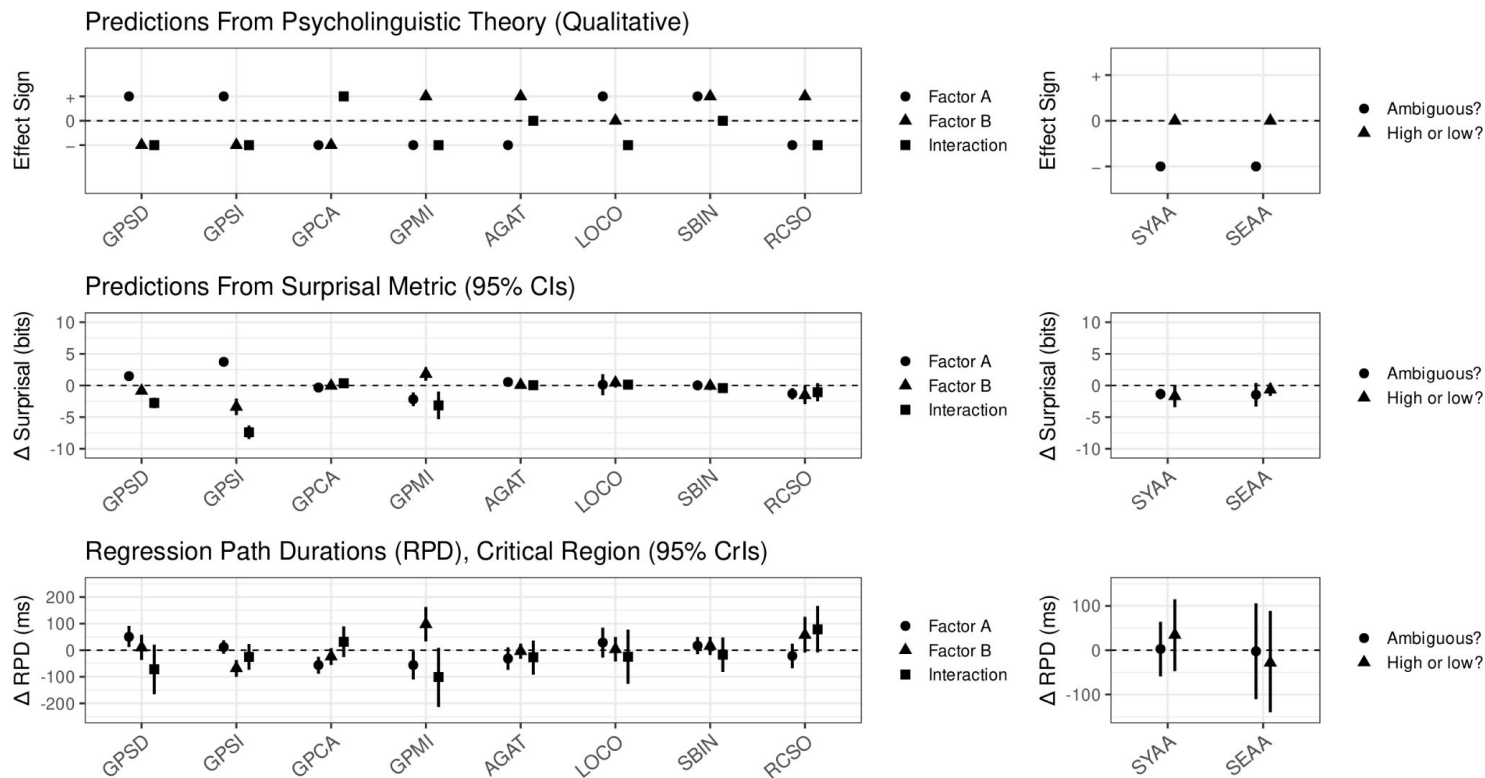
Self-Paced Reading Data, Critical Region (95% CIs)



4 Predictions and Observed Effects



4 Predictions and Observed Effects



5 Model Evaluation and Comparison



Models with single linear predictor ...

1. **Qualitative predictions** based on psycholinguistic theory (preregistered at osf.io/wpra9), encoding each predicted main effect / interaction as a 1-unit difference on the predictor
2. **Surprisal** (Hale 2001; Levy 2008) from GPT-2 (Radford et al. 2019)
3. **Lossy-context surprisal** (Futrell et al. 2021) from GPT-2, after probabilistic reconstruction of distorted context with BERT (Devlin et al. 2019) and Gibbs sampling

Evaluation method: Pareto-smoothed importance sampling (PSIS-LOO)

5 Model Evaluation and Comparison

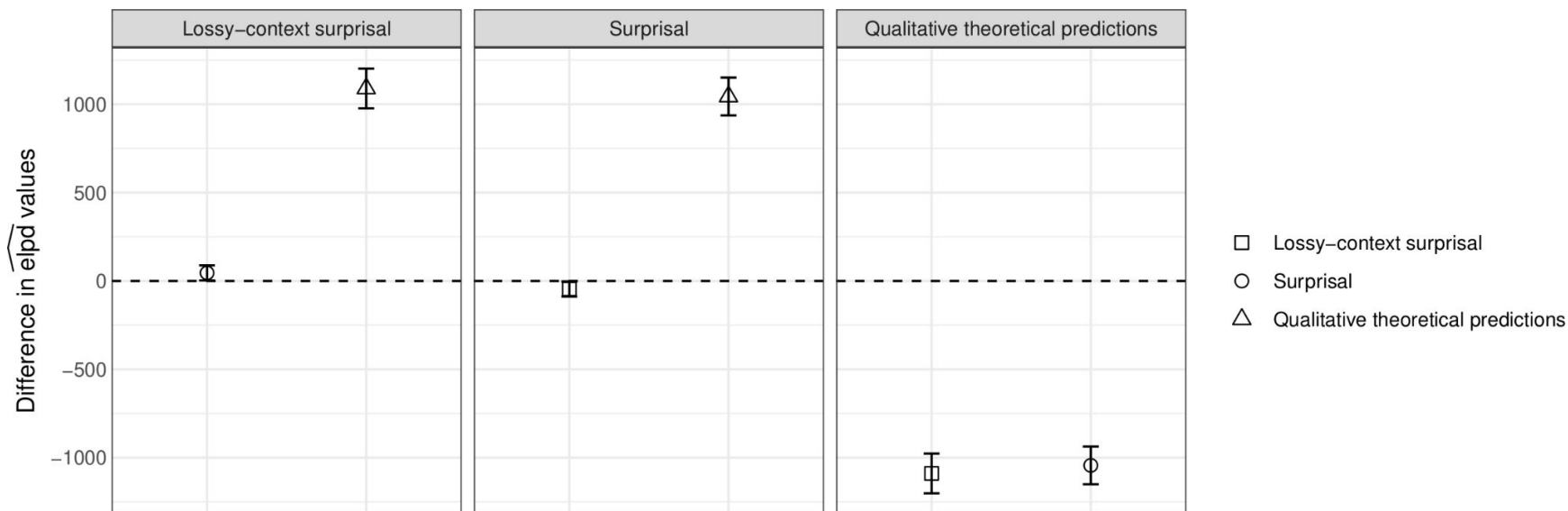
Self-paced reading ($N_{\text{included}} = 615$), reading times (RT) on critical region:

```
log(critical_RT) ~ predictor + (predictor | subject) + (predictor | phenomenon) + (predictor | phenomenon:item)
```

5 Model Evaluation and Comparison

Self-paced reading ($N_{\text{included}} = 615$), reading times (RT) on critical region:

$\log(\text{critical_RT}) \sim \text{predictor} + (\text{predictor} \mid \text{subject}) + (\text{predictor} \mid \text{phenomenon}) + (\text{predictor} \mid \text{phenomenon:item})$



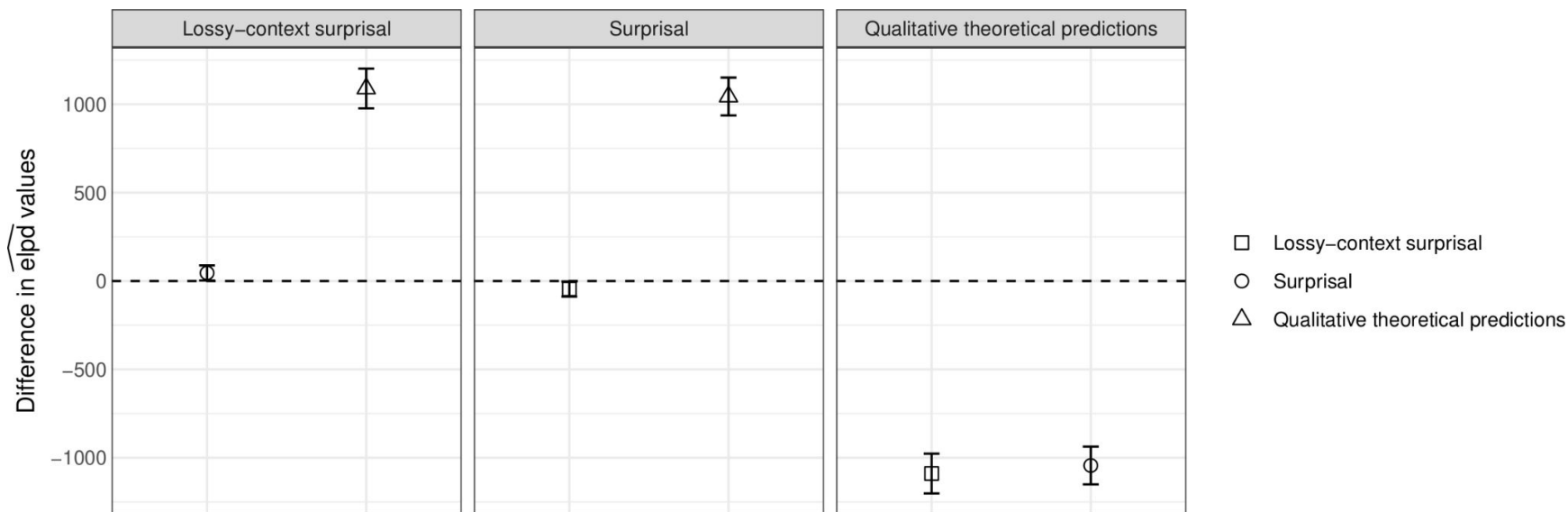
5 Model Evaluation and Comparison

Small, but significant edge of
lossy surprisal over plain surprisal.

Huge edge of **both** surprisal variants
over classical qualitative theory.

Self-paced reading ($N_{\text{included}} = 615$), reading times (RT) on critical region:

$\log(\text{critical_RT}) \sim \text{predictor} + (\text{predictor} \mid \text{subject}) + (\text{predictor} \mid \text{phenomenon}) + (\text{predictor} \mid \text{phenomenon:item})$



5 Model Evaluation and Comparison

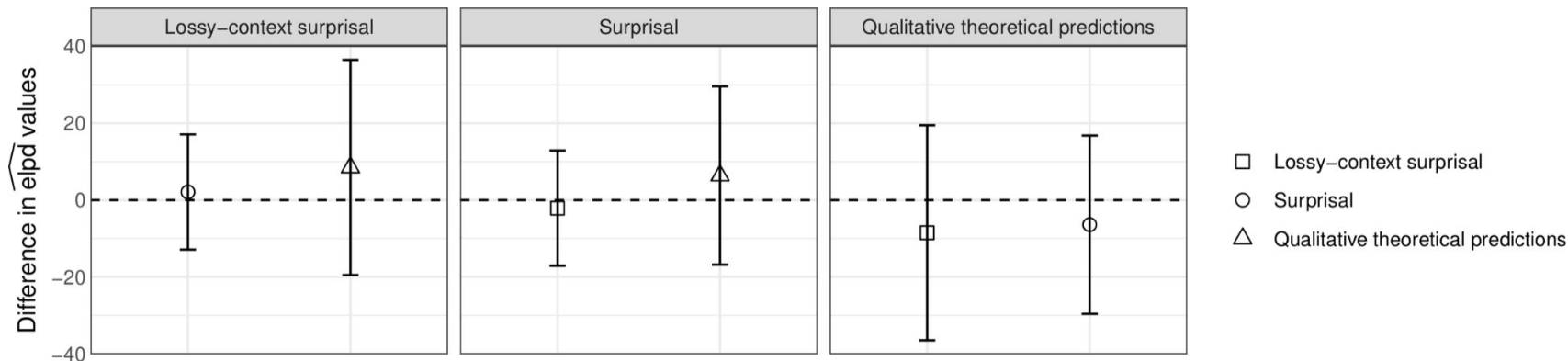
Eye tracking ($N_{\text{included}} = 118$), regression path durations (RPD) on critical region:

```
log(critical_RPD) ~ predictor + (predictor | subject) + (predictor | phenomenon) + (predictor | phenomenon:item)
```

5 Model Evaluation and Comparison

Eye tracking ($N_{\text{included}} = 118$), regression path durations (RPD) on critical region:

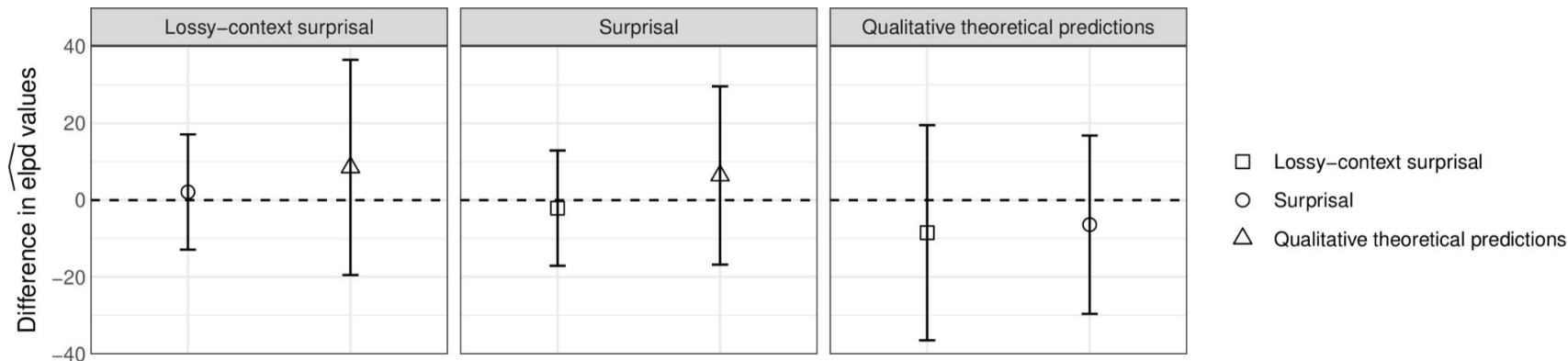
$\log(\text{critical_RPD}) \sim \text{predictor} + (\text{predictor} \mid \text{subject}) + (\text{predictor} \mid \text{phenomenon}) + (\text{predictor} \mid \text{phenomenon:item})$



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Eye tracking ($N_{\text{included}} = 118$), regression path durations (RPD) on critical region:

$\log(\text{critical_RPD}) \sim \text{predictor} + (\text{predictor} \mid \text{subject}) + (\text{predictor} \mid \text{phenomenon}) + (\text{predictor} \mid \text{phenomenon:item})$

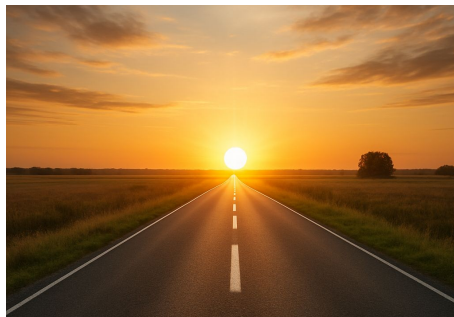


There is no evidence yet favoring one model over the others.

6 Future Directions

The **final dataset** will be **openly available**.

More **model evaluations** are planned, e.g, on resource-rational lossy surprisal (Hahn et al., 2022) or cognitive process models.



Thanks for your attention!



References [1/2]



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