

Comprehenders aggregate over speakers when adapting to the noise in the input

Rachel Ryskin^{1,2} (ryskin@mit.edu), Richard Futrell³, Swathi Kiran², Edward Gibson¹

1. MIT, 2. Boston U, 3. UC Irvine

Introduction

- ▶ In everyday communication, speakers/writers make errors & listeners/readers mishear.
- ▶ Comprehenders may deal with noise in the linguistic signal by integrating prior information about the probability of a sentence with an implicit model of how noise affects utterances (Gibson et al., 2013; Levy, 2008; Levy et al., 2009).
- ▶ In conversation, speakers have different error patterns (e.g., a child and an L2 speaker)
- ▶ The noise model is adapted to the nature of noise in the environment (Ryskin et al., 2018)
- ▶ **Question:** Do readers maintain and update multiple, speaker-specific noise models or do they continuously update a single noise model?

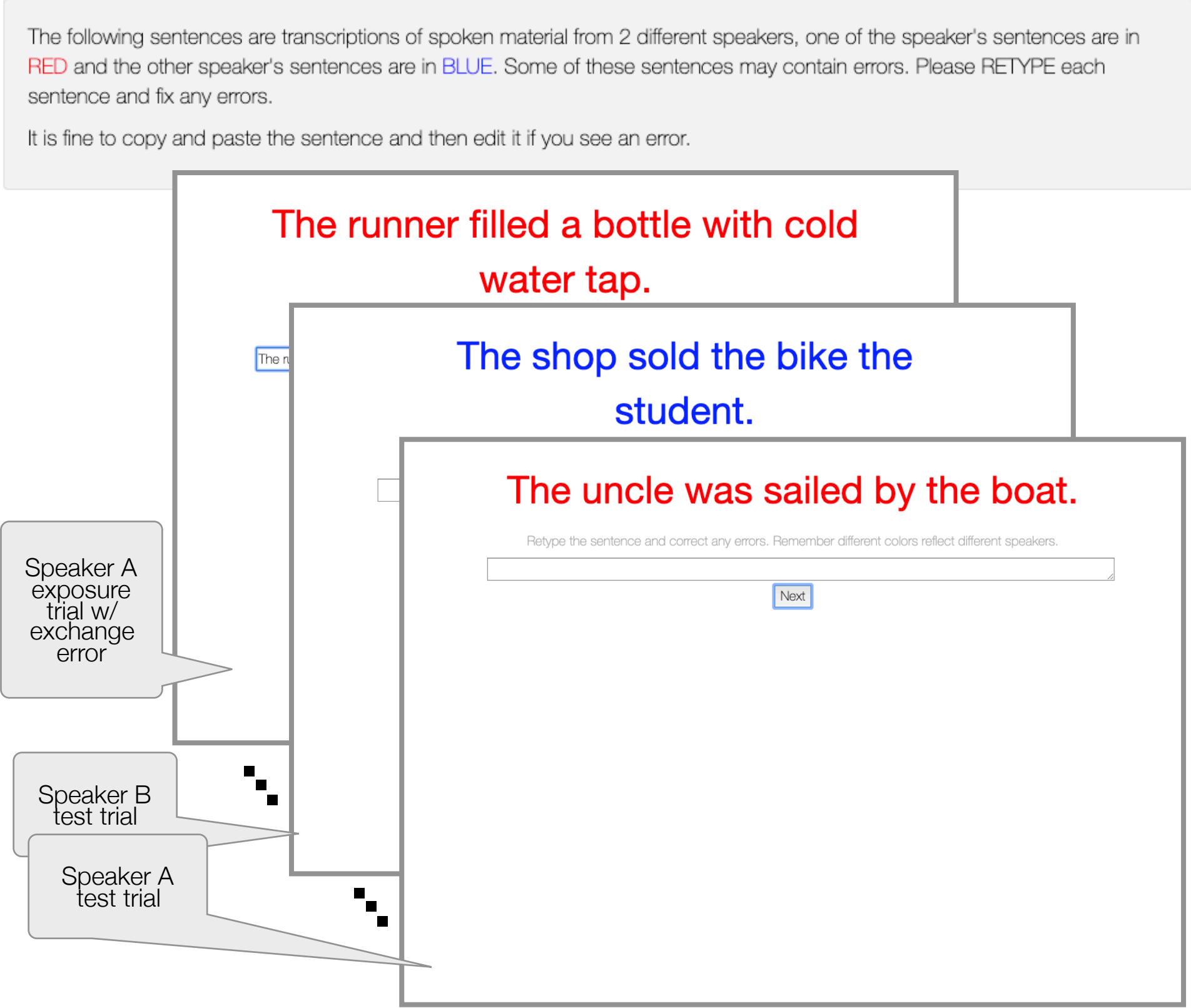
Methods

osf.io/n25wk/

- ▶ N=987 English speakers on psiTurk / Amazon's Mechanical Turk
- ▶ Re-typing task w/ sentences :
 - ▶ **12 test** sentences (syntactically licit, semantically implausible)
 - ▶ **18 exposure** sentences containing < deletion | insertion | exchange | mixed > errors
 - ▶ 60 fillers (plausible sentences, no errors)

x 2 Speakers

Speaker A exposure	Speaker B exposure	Lists
Deletion	Exchange	1
Deletion	Insertion	2
Deletion	Mixed	3
Exchange	Deletion	4
Exchange	Insertion	5
Exchange	Mixed	6
Insertion	Deletion	7
Insertion	Exchange	8
Insertion	Mixed	9
Mixed	Deletion	10
Mixed	Exchange	11
Mixed	Insertion	12



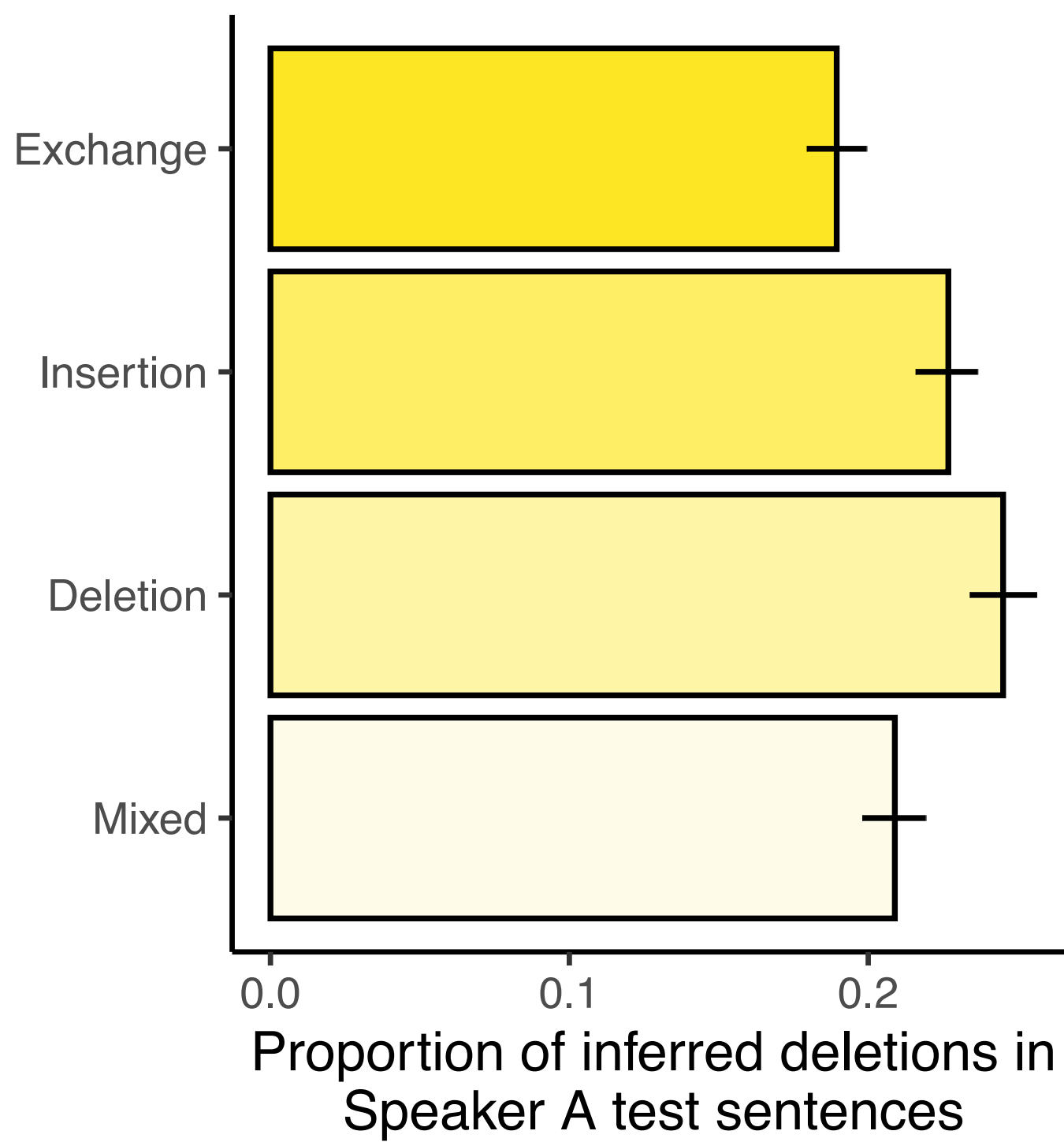
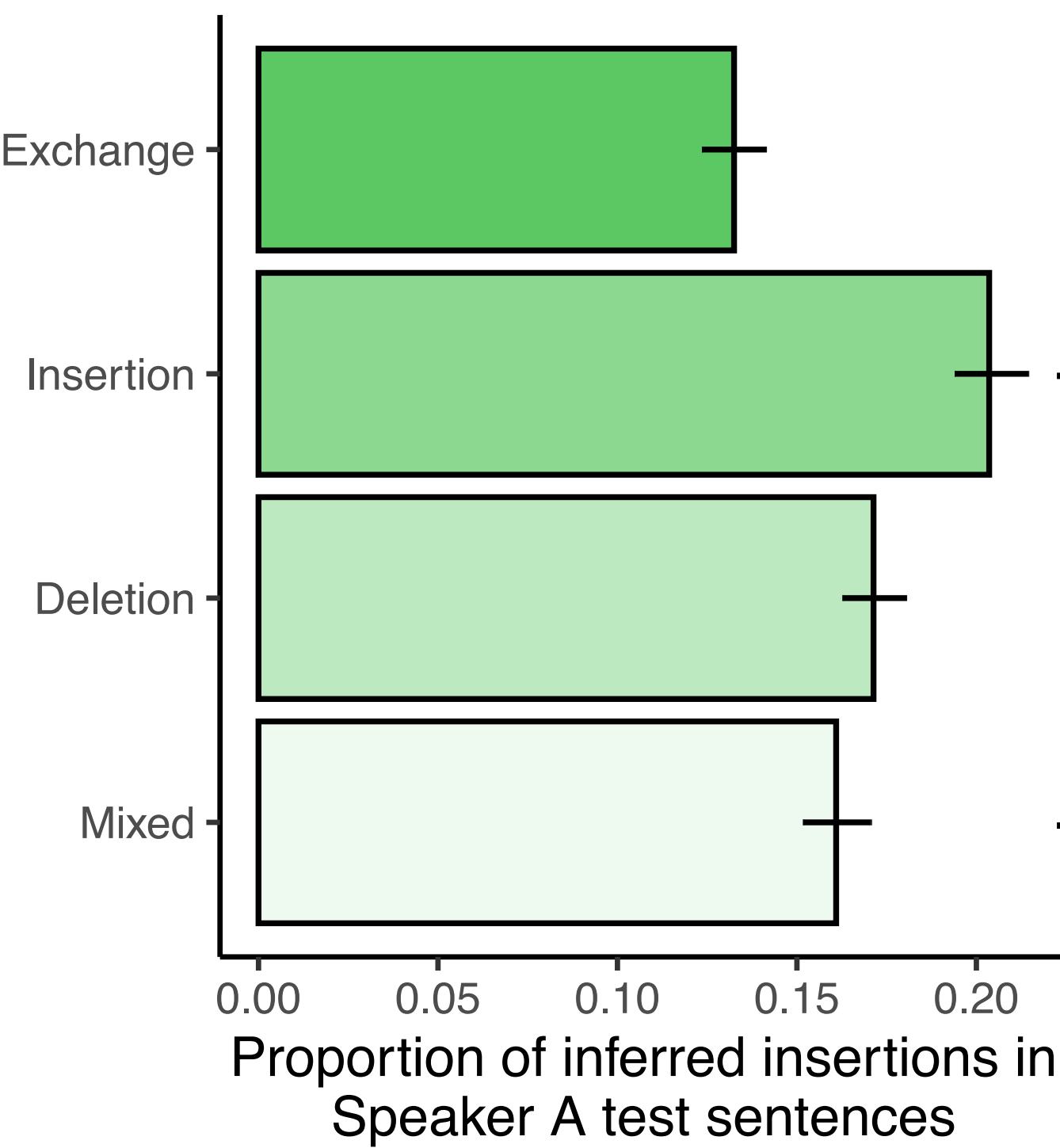
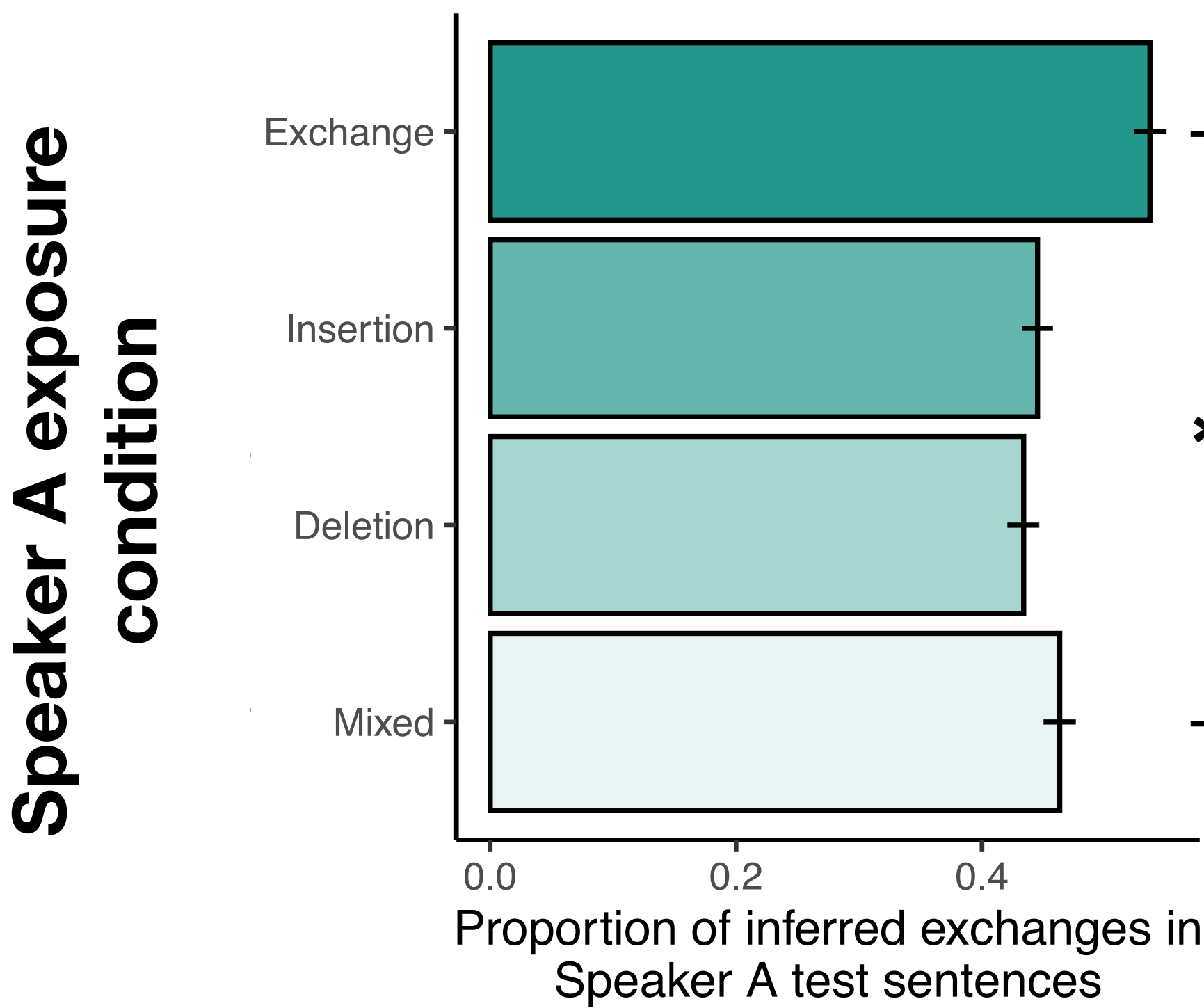
Results

Proportion of responses of each type

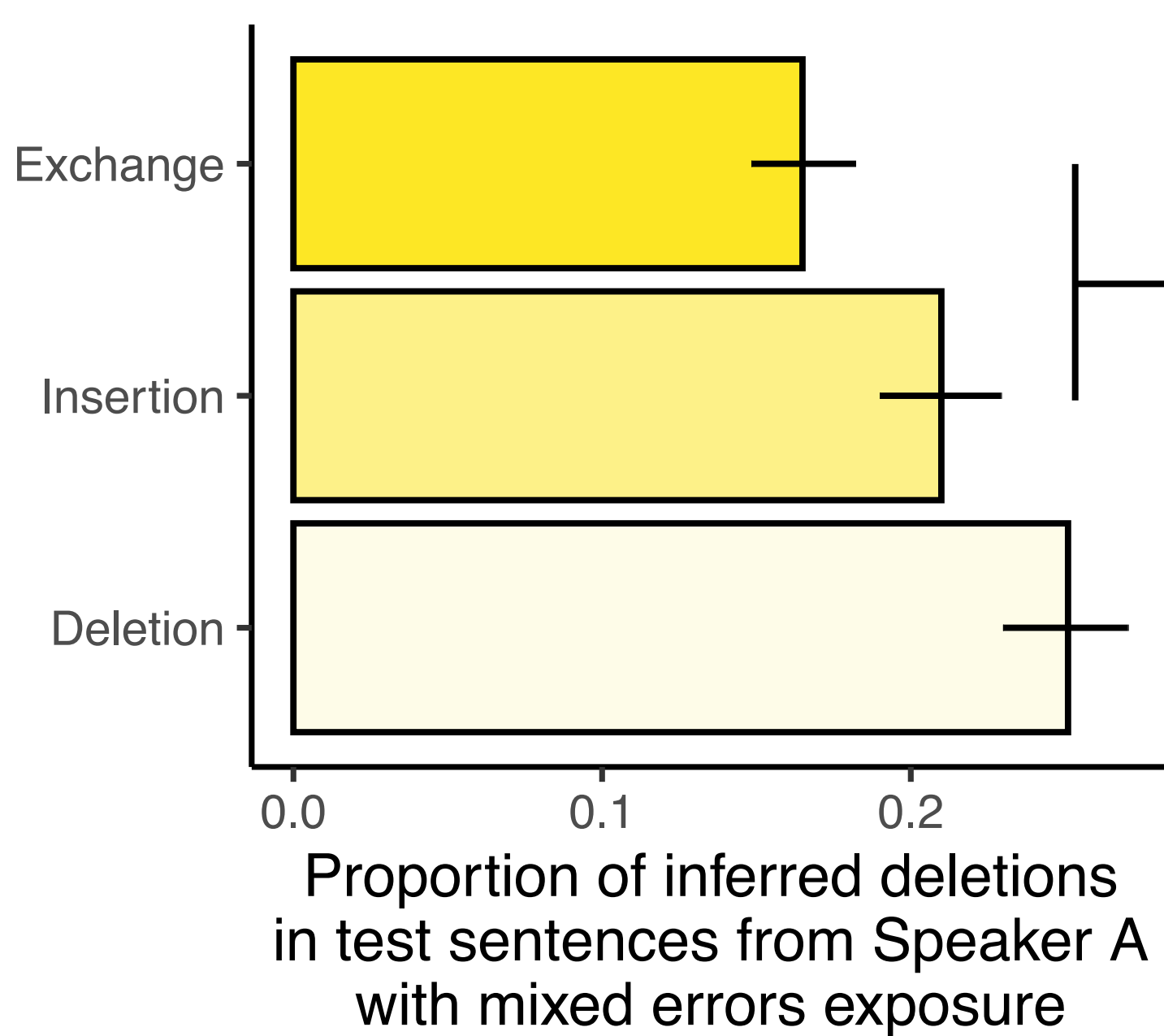
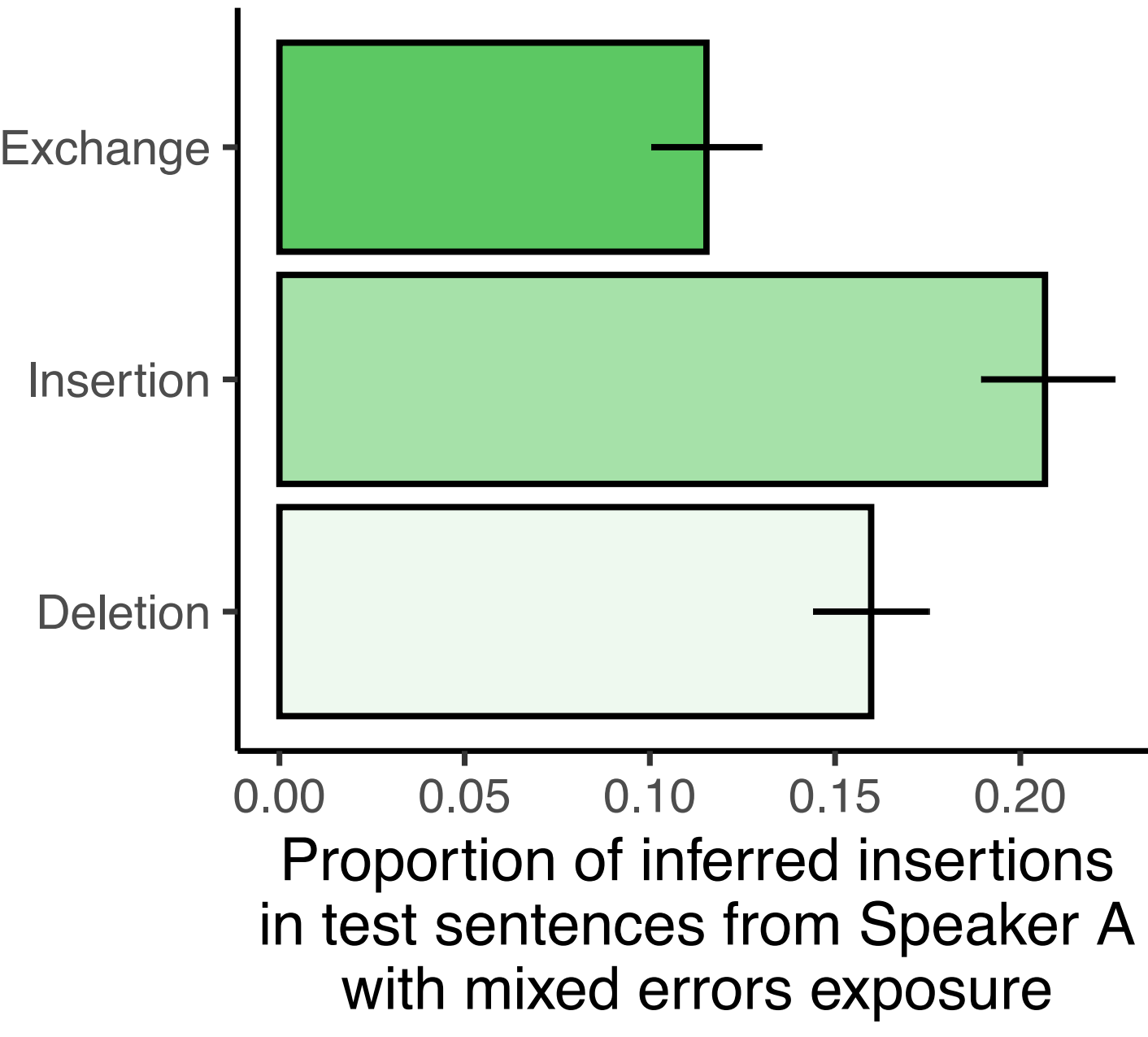
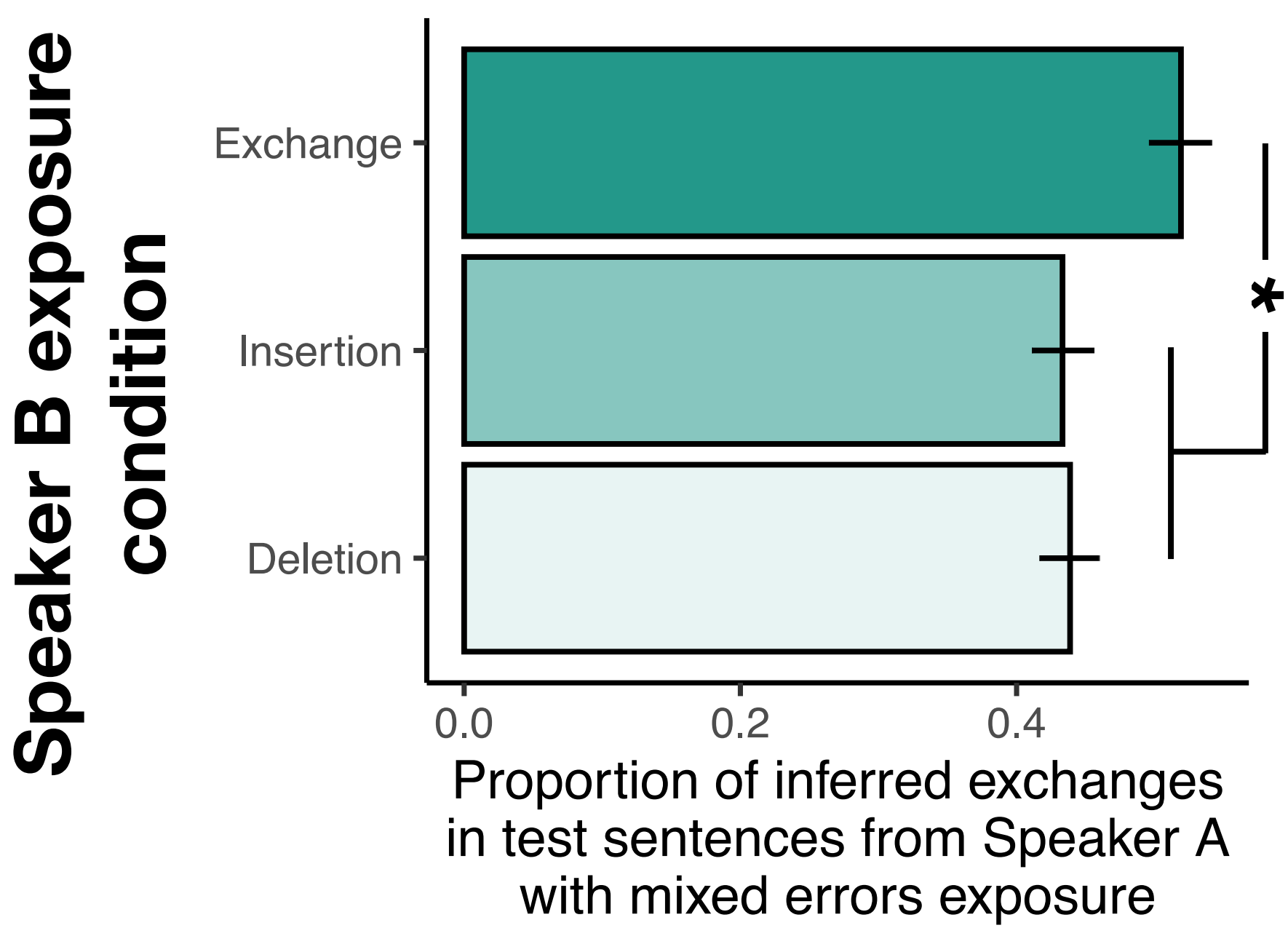


- ▶ Inferred deletion (participant added a word during re-typing)
- ▶ Inferred insertion (participant deleted a word during re-typing)
- ▶ Inferred exchange (participant exchanged two words during re-typing)
- ▶ Inferred no error (participant made no changes during re-typing)
- ▶ Inferred other (participant made other change during re-typing)

(1) When correcting test sentences for Speakers A & B, participants were most likely to infer that there had been an exchange.



(2) When correcting test sentences for Speaker A, participants were more likely infer that there had been an exchange, insertion, or deletion when Speaker A was in the exchange, insertion, or deletion exposure condition respectively, relative to the mixed exposure condition



(3) When correcting test sentences for Speaker A - mixed exposure condition, participants were most likely to infer that there had been an exchange, insertion, or deletion when Speaker B was in the exchange, insertion, or deletion exposure condition respectively.

Conclusions

- ▶ On test sentences for Speaker A, participants' corrections were adapted to the types of errors that Speaker A was producing (replicating Ryskin et al., 2018), but were also affected by the errors produced by Speaker B.
- ▶ Ps tune their noise model to the distribution of errors in the input but, here, they aggregate input statistics over speakers.
- ▶ Benefit of greater context/speaker-specificity — more accurate noisy-channel correction — may be outweighed by the cost of added model complexity.

Funding: NIDCD F32 DC015163 to RR