

Conducting speech perception experiments online: Some tools, success, and challenges

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osf.io/8krg3/

For a more in-depth tutorial, visit:

<https://tinyurl.com/Online-Perception-Tutorial>

Tools

Prolific

- <https://www.prolific.co>
- Online participant pool
- Large, diverse sample
- Researchers can apply filters to determine who has access to a study
- Prolific is built to provide high quality data and promote ethical treatment of participants
- Researchers are charged a fee based on payment to participant



Gorilla

- <https://gorilla.sc>
- Software to build experiments
- Server to host online studies
- If you can dream it, Gorilla can build it
- Supports collaboration, open materials, version control, data management
- Free to build; charged a “token” to download data for each subject



Headphone screen

- Woods et al. (2017), *Attention, Perception, & Psychophysics*
- Six-trial screen; 5 correct responses == “Pass”
- Task is choosing which of three tones is quietest
- Tone sequences manipulate phase across stereo channels
- Vetting data show reasonable sensitivity for detecting headphone use, in my opinion



/mcdermottLab

General procedures to facilitate success

- Design the experiment to be only as long as needed, we aim for ≤ 20 minutes
 - Data quality is better for shorter tasks
 - Subjects make their own break(s) in longer tasks
- Convert sound files to MP3 and image files to JPEG; *provide clear instructions regarding auto-play and headphone requirements*
- Give people at least two chances to pass the headphone screen, with a friendly reminder of headphone requirement between screens
- Pay well; we compensate at \$10/hour

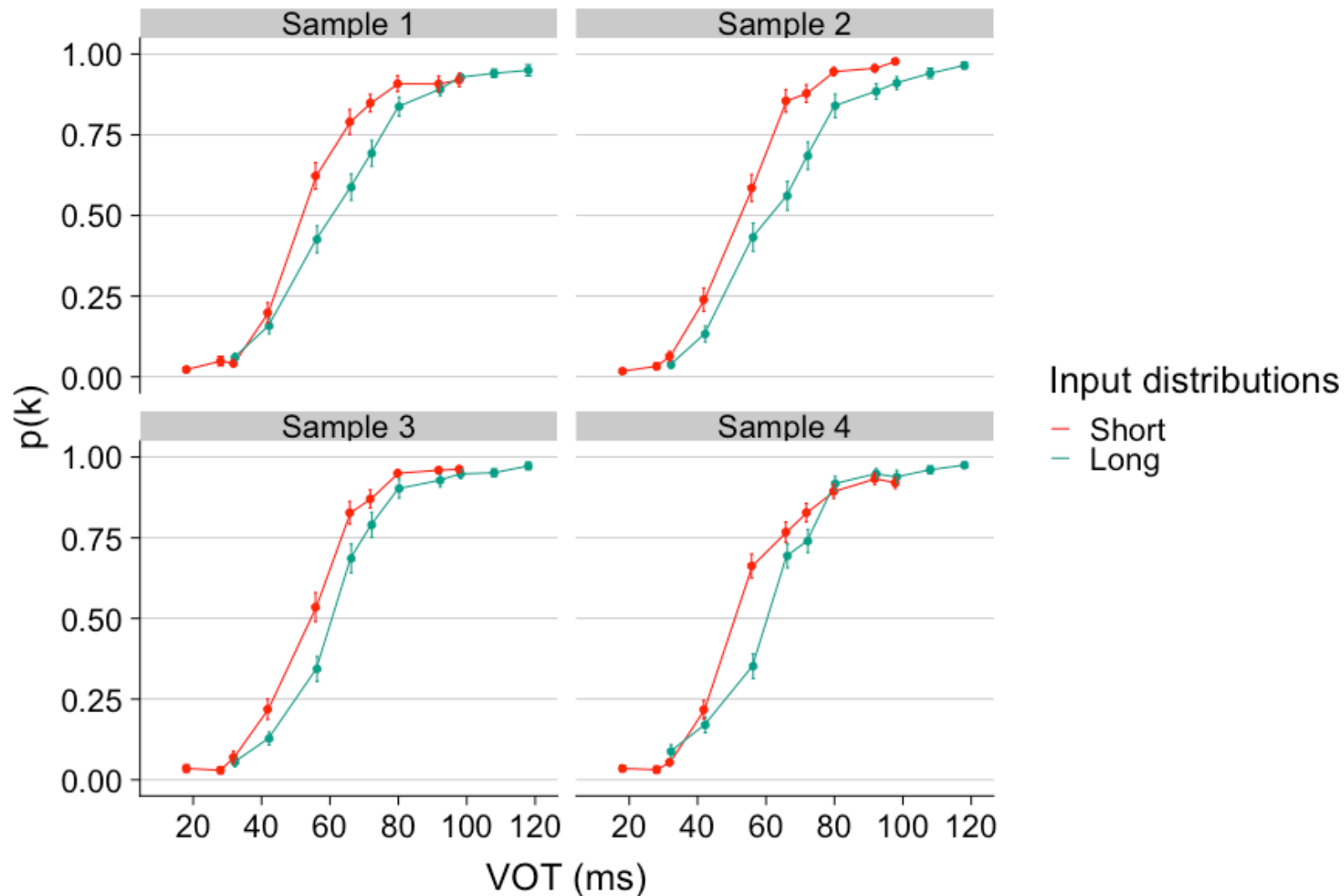
Success 1: Categorical perception/distributional learning

Block 1

- 152 trials of phonetic ID for tokens drawn from a VOT continuum to form either short or long VOT input distributions

Block 2

- 152 trials of phonetic ID for tokens drawn from a VOT continuum to form either short or long VOT input distributions



To achieve sample ($n = 320$), we excluded $n = 52$ due to failure to perform the task and $n = 27$ due to failure to pass headphone screen; attrition = 20%.

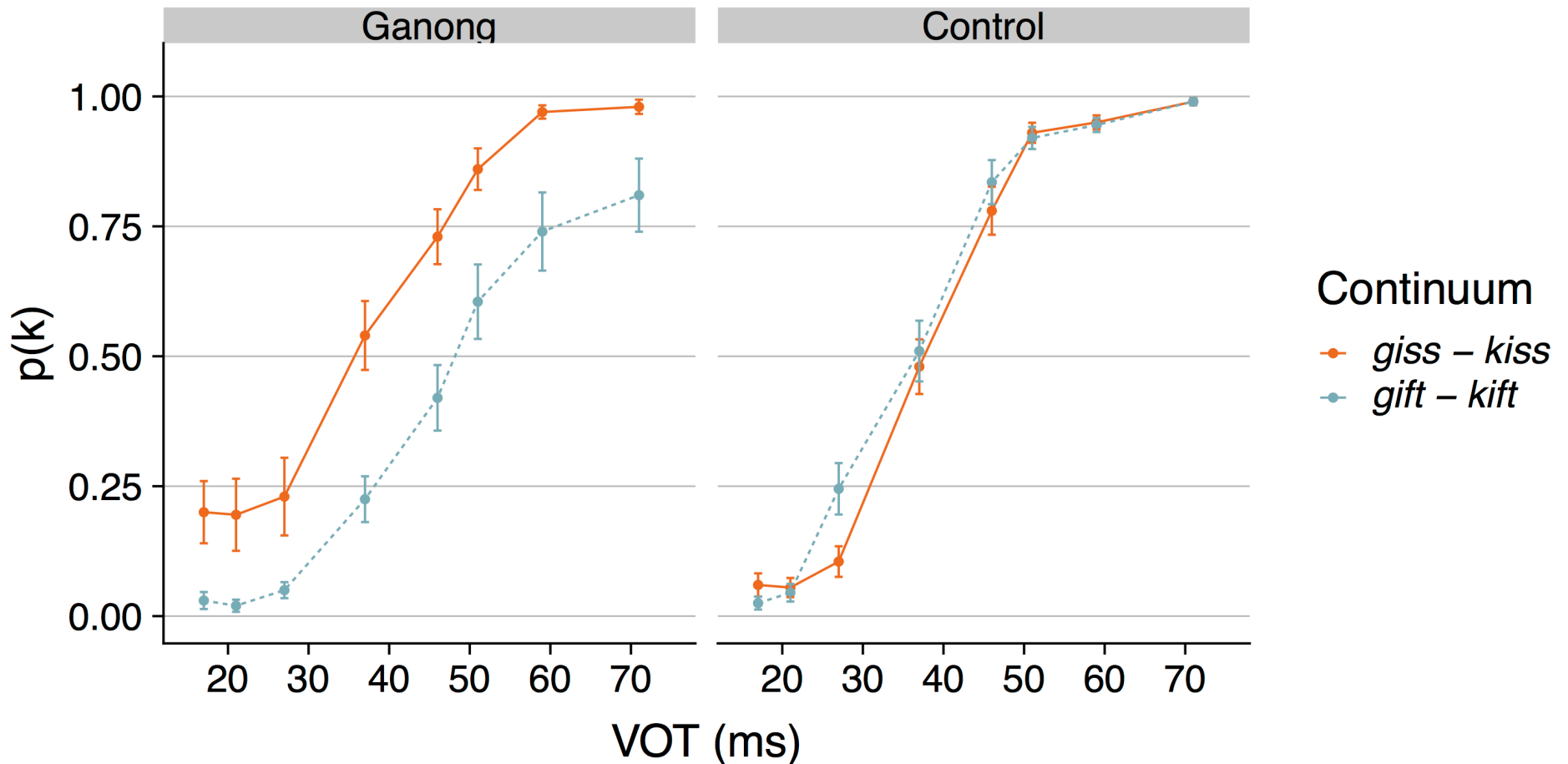
Success 2: Ganong effect

Block: Ganong

- 160 trials of phonetic ID for *gift-kift* and *giss-kiss* VOT continua

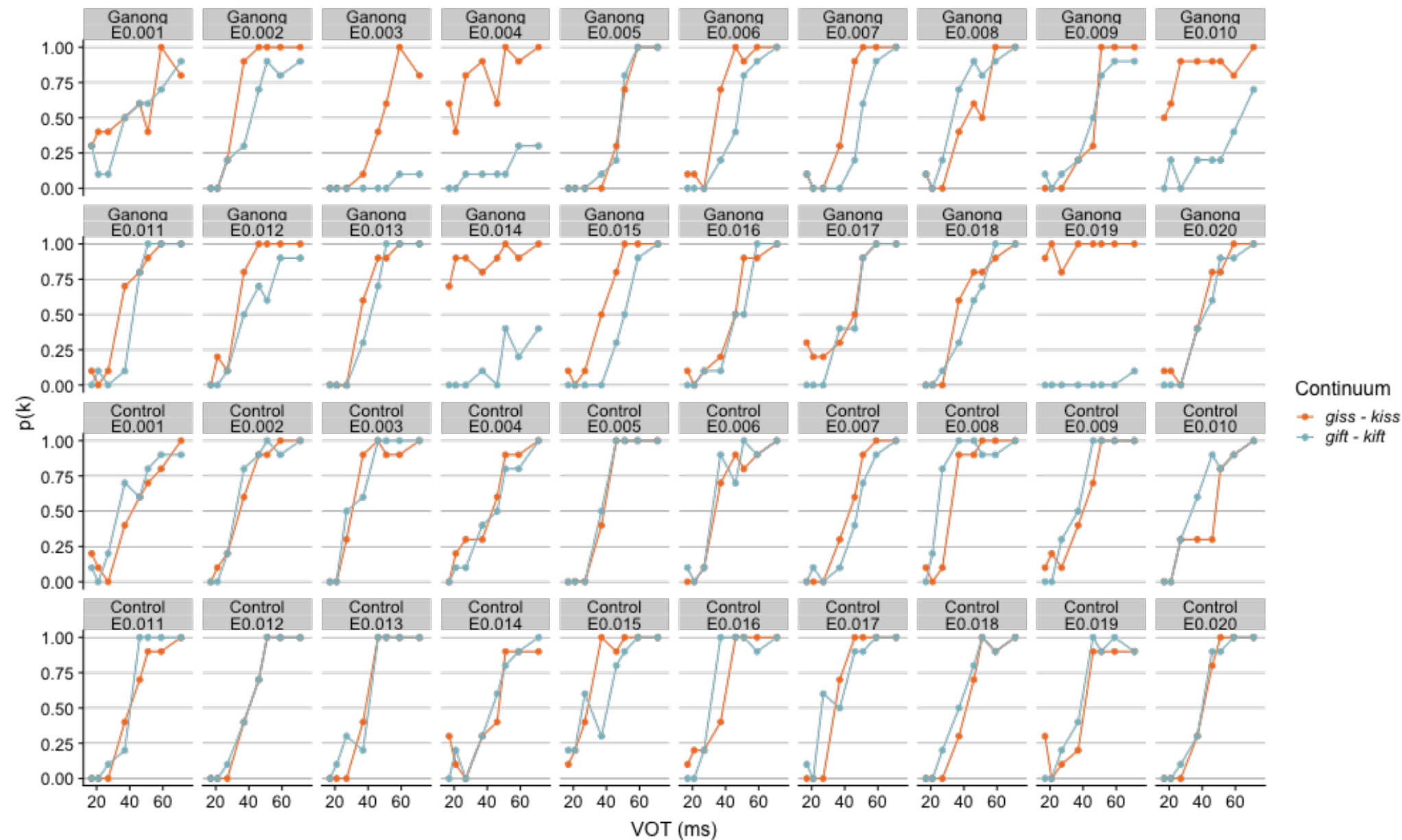
Block: Control

- 160 trials of phonetic ID for the same VOT continua, excising disambiguating lexical information



To achieve sample ($n = 20$), we excluded $n = 0$ due to failure to perform the task and $n = 3$ due to failure to pass headphone screen; attrition = 13%.

Success 2: Ganong effect



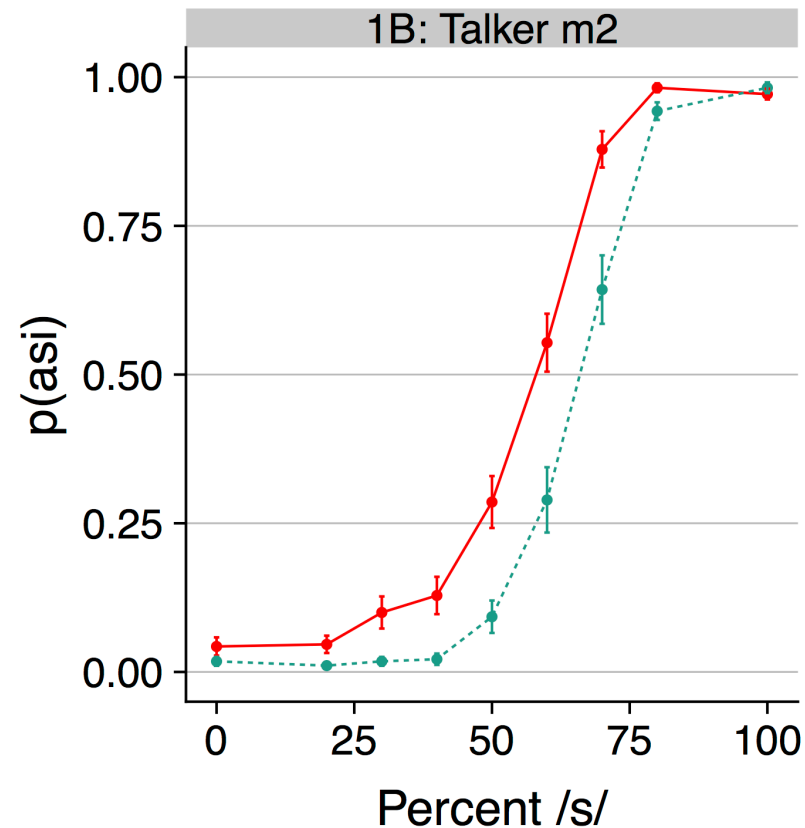
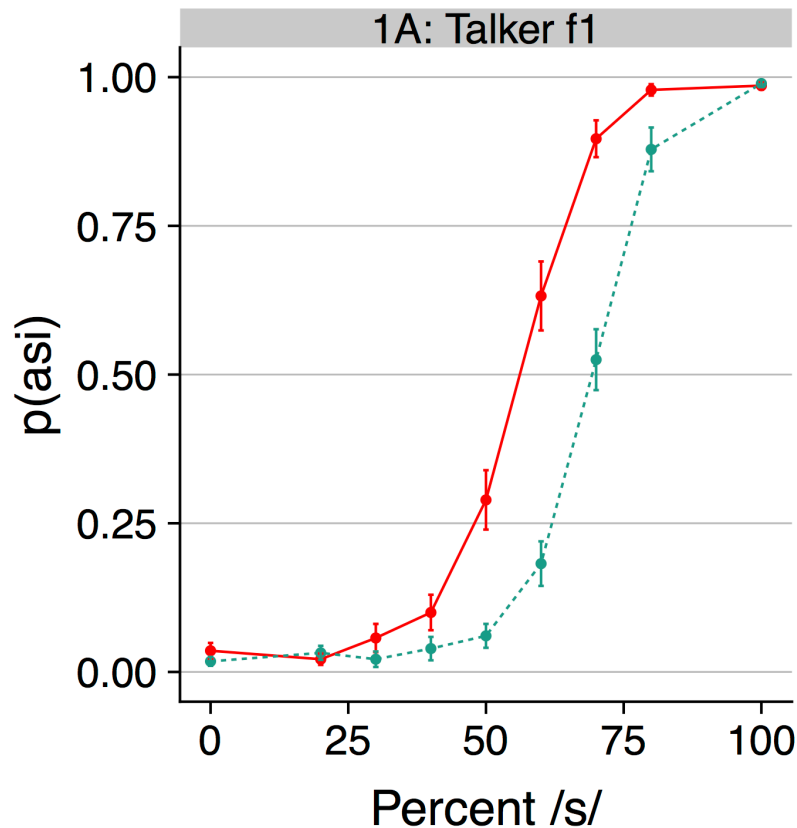
Success 3: Lexically guided perceptual learning

Block: Exposure

- 200 trials of a lexical decision task for word and nonword stimuli; critical ambiguous productions embedded in either /s/ or /ʃ/ biasing contexts

Block: Test

- 72 trials of phonetic ID for tokens drawn from an /asi/-/afi/ continuum



To achieve sample ($n = 560$), we excluded $n = 32$ due to failure to perform the task and $n = 112$ due to failure to pass headphone screen; attrition = 20%.

Success 4: Perceptual learning for vocoded speech

Block: Pre-test

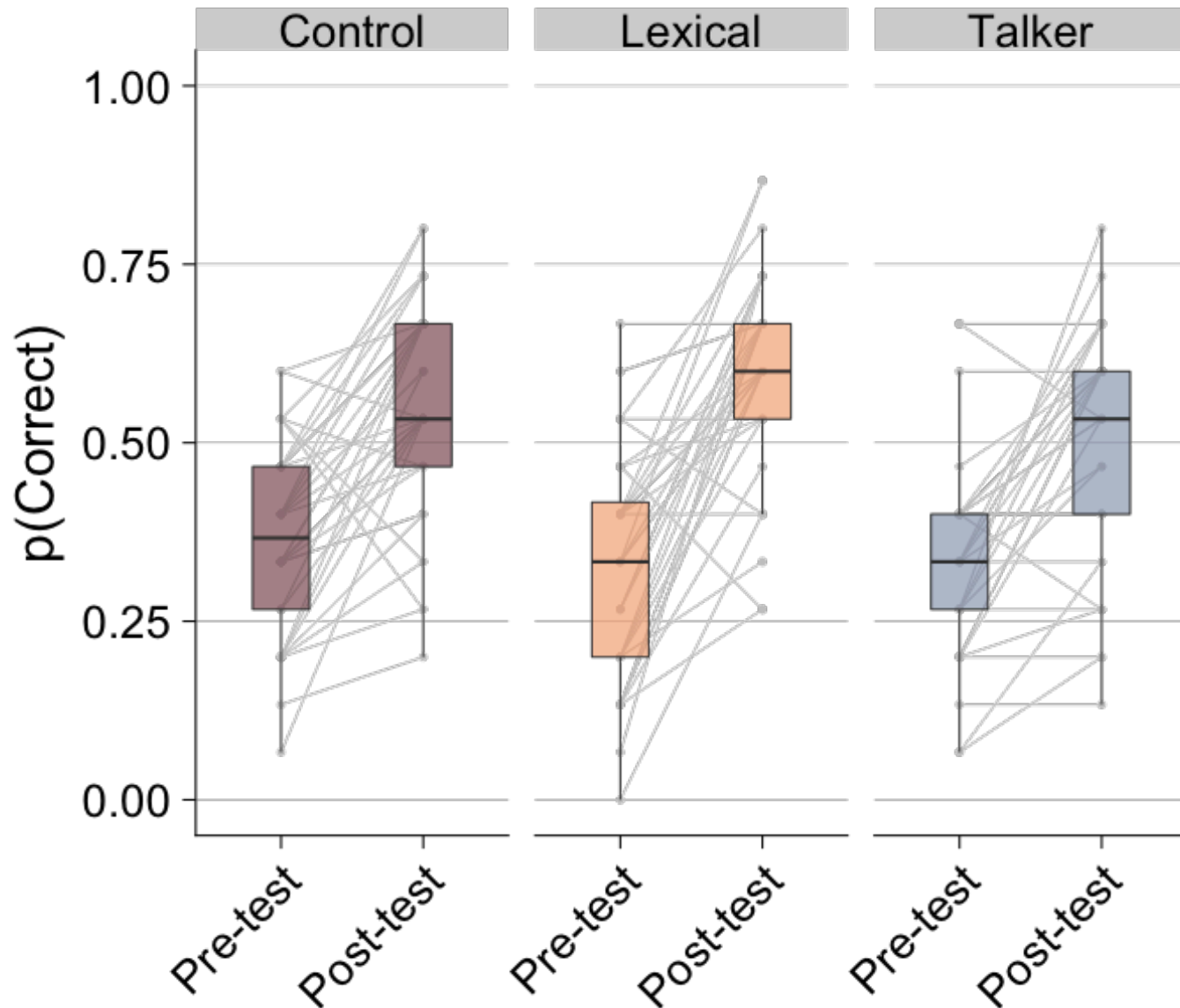
- 30 trials of a transcription task for vocoded sentences w/o feedback

Block: Training

- 150 trials with vocoded sentences
 - *Control*: Sentence transcription w/o feedback
 - *Lexical*: Sentence transcription w/ feedback
 - *Talker*: Talker ID w/ feedback

Block: Post-test

- 30 trials of a transcription task for vocoded sentences w/o feedback

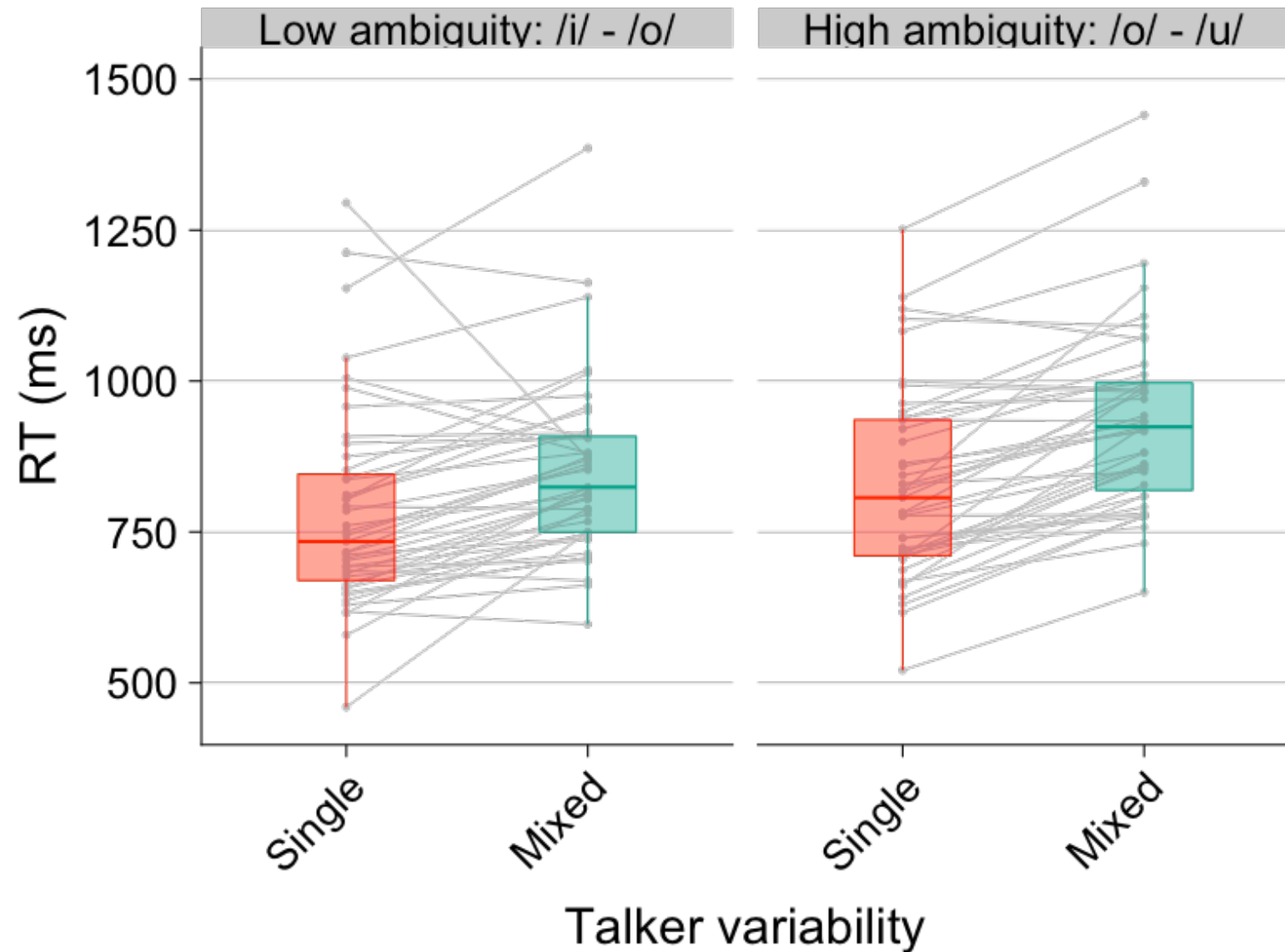


To achieve sample ($n = 108$), we excluded $n = 2$ due to failure to perform the task and $n = 12$ due to failure to pass headphone screen; attrition = 11%.

Success 5: Talker normalization/phonemic ambiguity

Blocks: Word ID

- 160 trials of speeded word ID distributed across four separate blocks, formed by crossing phonemic ambiguity and talker variability



To achieve current sample (n = 44), we excluded n = 4 due to failure to perform the task and n = 10 due to failure to pass headphone screen; attrition = 24%.

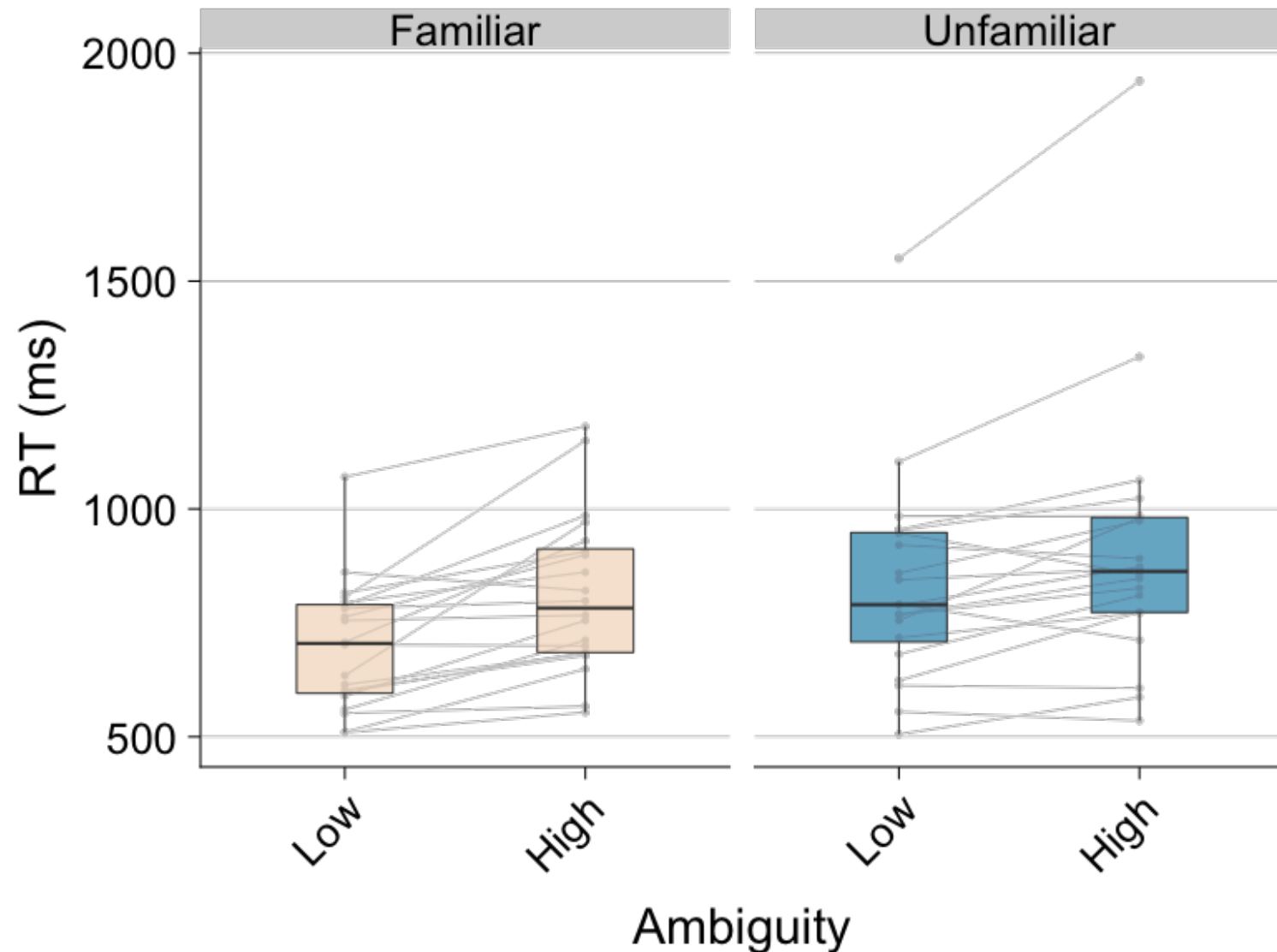
Success 6: Talker familiarity

Block: Familiarization

- 40 trials of talker ID task w/ feedback; Familiar vs. Unfamiliar listener groups

Block: Test

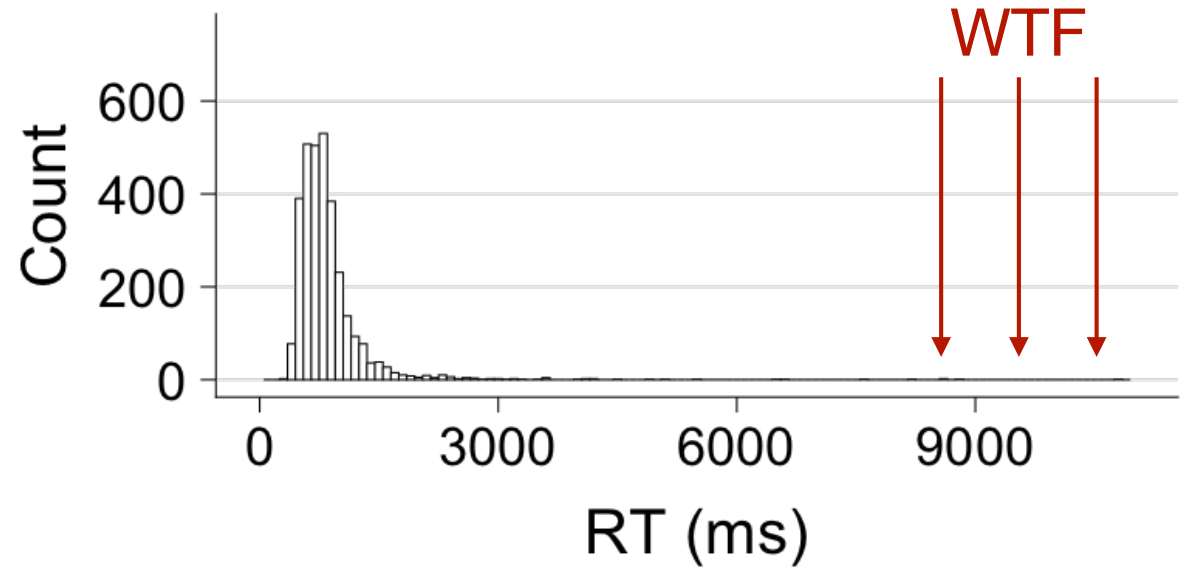
- 80 trials of speeded word ID distributed across two separate blocks; one for a low ambiguity contrast (*heed* vs. *hoed*) and one for a high ambiguity contrast (*hoed* vs. *who'd*)



To achieve current sample (n = 40), we excluded n = 3 due to failure to perform the task and n = 12 due to failure to pass headphone screen; attrition = 27%.

Success 6: Talker familiarity

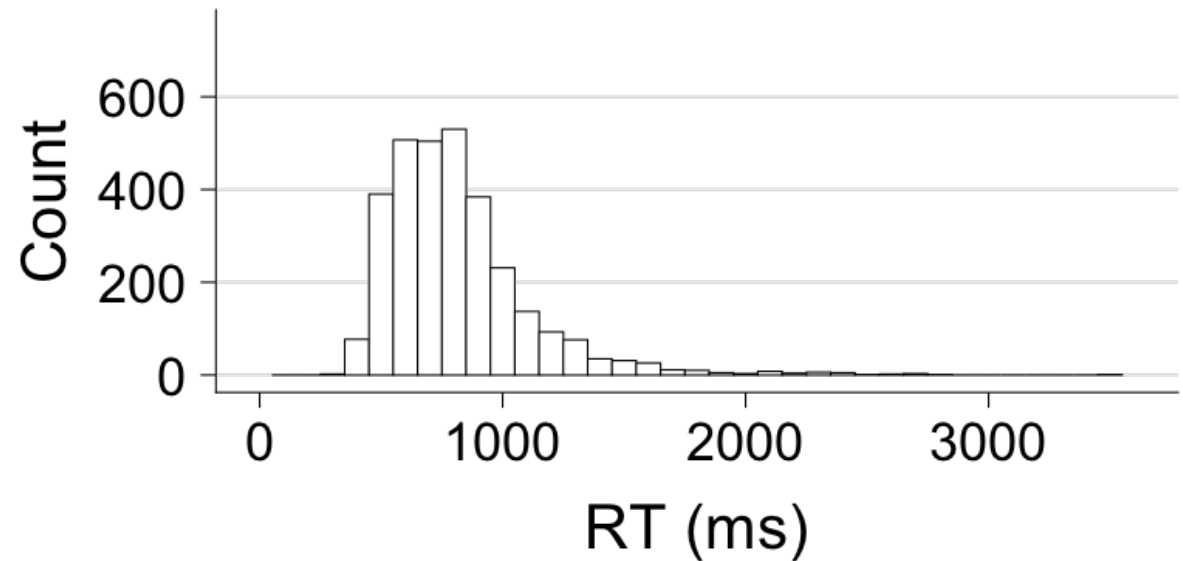
Distribution of RTs for 3,140 correct responses

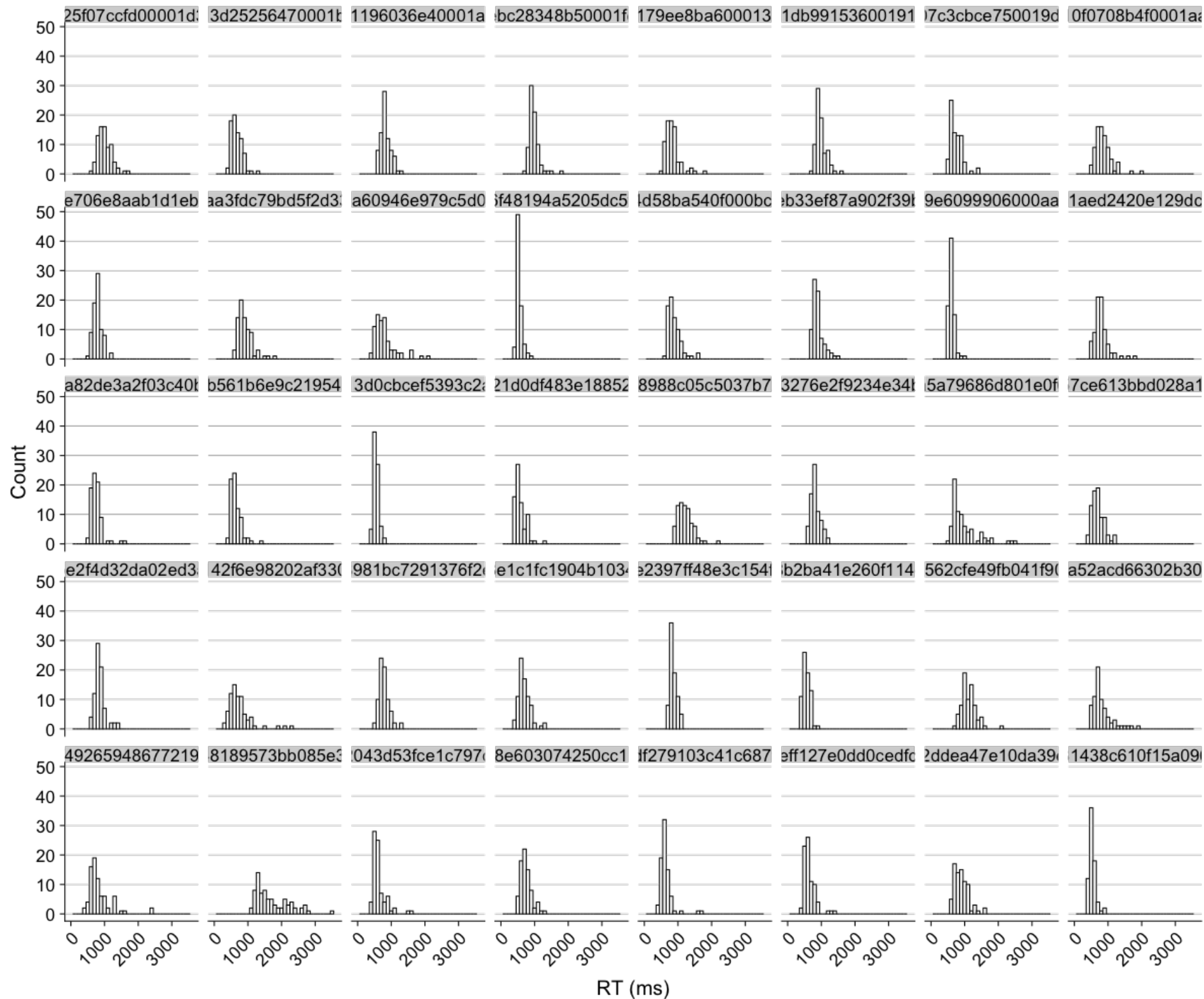


Distribution of RTs excluding:

- RTs > 5000 ms
- RTs exceeding 3 SDs of each subject's mean RT

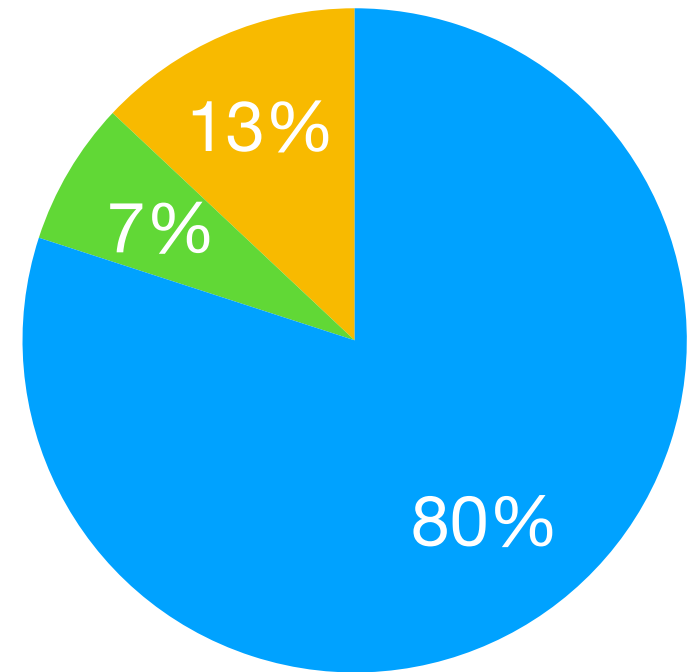
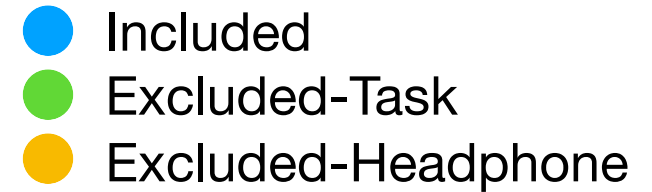
*Removes 1.8% of the data
(56 of 3140 trials)*





Challenges: Headphone compliance

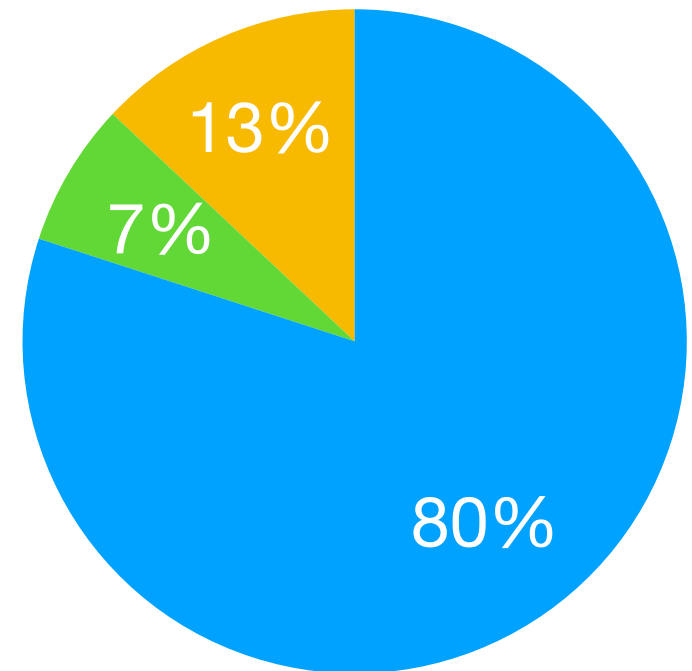
- Headphone compliance is the greatest source of attrition
- Loss of 176 participants for the studies presented here
- *Specificity* of the Woods et al. (2017) screen?
- Dear Prolific, please let us compensate people for the headphone screen, and then route them out of the study



Challenges: Bots/low-effort participants

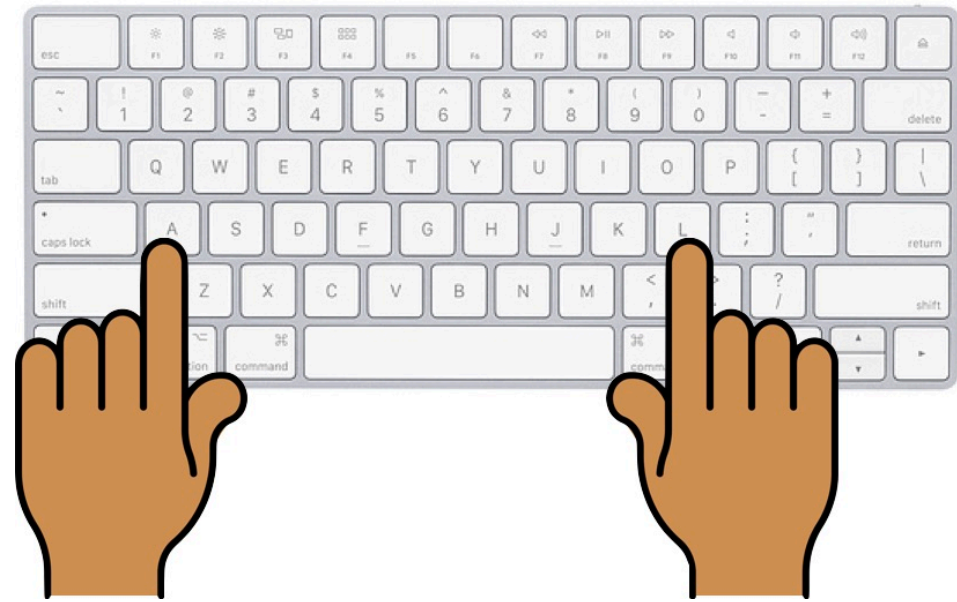
- Bots and low-effort participants are rare in Prolific, and fairly easy to detect
 - Are many RTs < 5 ms?
 - Are RTs *too* consistent?
 - Is accuracy at chance?
 - Do you see logistic response functions where expected?
- When possible, design studies that support bot detection

● Included
● Excluded-Task
● Excluded-Headphone



Challenges: RT as a dependent measure

- RT experiments pose unique challenges
- Timing accuracy/variability for sound presentation; how can we constrain it?
- Need to develop clear, *a priori* inclusion and outlier criteria
- Use within-subjects manipulations when you can





Behavioural Science Online

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