1   Unravelling the time-course of listener adaptation to an unfamiliar talker.

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10 Abstract

11 YOUR ABSTRACT GOES HERE. All data and code for this study are shared via OSF,

12 including the R markdown document that this article is generated from, and an R library that

13 implements the models we present.

14 *Keywords:* speech perception; perceptual adaptation; distributional learning; ...

15 Word count: X

16   Unravelling the time-course of listener adaptation to an unfamiliar talker.

17   TO-DO

0.1   Highest priority

- MARYANN

0.1.1   Priority

- FLORIAN

0.2   To do later

- Everyone: Eat ice-cream and perhaps have a beer.

1 Introduction

Talkers vary in the way they realise linguistic categories. Yet, listeners who share a common language background typically cope with talker variability without difficulty. In scenarios where a talker produces those categories in an unexpected and unfamiliar way comprehension may become a real challenge. It has been shown, however that brief exposure to unfamiliar accents can be sufficient for the listener to overcome any initial comprehension difficulty (e.g. Bradlow & Bent, 2008; Clarke & Garrett, 2004; X. Xie, Liu, & Jaeger, 2021; X. Xie et al., 2018). This adaptive skill is in a sense, trivial for any expert language user but becomes complex when considered from the angle of acoustic-cue-to-linguistic-category mappings. Since talkers differ in countless ways and each listening occasion is different in circumstance, there is not a single set of cues that can be definitively mapped to each linguistic category. Listeners instead have to contend with many possible cue-to-category mappings and infer the intended category of the talker. How listeners achieve prompt and robust comprehension of speech in spite of this variability (the classic "lack of invariance" problem) remains the a longstanding question in speech perception research.

In the past two decades the hypothesis that listeners overcome the lack of invariance by learning the distributions of talkers' acoustic cue-to-linguistic category mappings has gained considerable influence in contemporary approaches to studying this problem. A growing number of studies have demonstrated that changes in listener behaviour through the course of a short experiment align qualitatively with the statistics of exposure stimuli (Clayards, Tanenhaus, Aslin, & Jacobs, 2008a; Cummings & Theodore, 2023 etc; Kleinschmidt & Jaeger, 2015, 2016; Theodore & Monto, 2019).

- For example when listeners are tasked with identifying word pairs like *beach-peach* contrasted by the voice-onset-time (VOT) cue they would exhibit categorisation behaviour that corresponds to the properties of the distributions from which these words are sampled. Listeners exposed to tokens from distribution with wide variances tend to have categorisation functions that are shallower than listeners who hear words sampled from a narrow variance (Clayards et al. (2008a); Theodore and Monto (2019)). In such paradigms, the means the categories are held constant usually at locations where listeners would expect.

52   This is motivated by hypotheses that listeners implicit knowledge about spoken language

53   • When mean values are moved away from listener. Kleinschmidt and Jaeger (2016) tested

54   listener on a wide range of /b-p/ distributions with means at different locations relative to

55   the expected means.

56   • THE AIM OF THIS STUDY- The study we report here builds on the pioneering work of

57   Clayards et al. (2008a) and Kleinschmidt and Jaeger (2016) with the aim to shed more light

58   on how listeners' initial interpretation of cues from a novel talker incrementally change as

59   they receive progressively more informative input of her cue-to-category mappings.

60   POINTS-TO-MAKE

61   • Most of the work has focused on the outcome of exposure.

62   • Qualitatively, we know that exposing listeners to different distributions produces changes in

63   categorisation behaviour towards the direction of the shifts.

64   • A stronger test for the computational framework is needed.

65   • The ideal adapter framework makes specific predictions about rational speech perception.

66   For example, listeners' integrate the exposure with their prior knowledge and infer the

67   cue-category distributions of a talker. Listeners hold implicit beliefs or expectations about

68   the distributions of cues which they bring to an encounter.

69   • The strength of these beliefs has bearing on listener propensity to adapt to a new talker –

70   the stronger the prior beliefs the longer it takes to adapt. Listeners' strengths in prior

71   beliefs about the means and variances are represented by parameters in the computational

72   model. Listener behaviour observed collectively, thus far which speaks to this framework of

73   thinking should by now be able to indicate roughly what those parameter values are. But it

74   looks like those parameters are biased by the length of exposure and the outcome during

75   experiments. No one has confronted this issue of very quick but limited adaptation which

76   can't be solved by giving more exposure trials.

77   • How do we distinguish the results from normalization accounts which can also explain

78   adaptation but is not usually regarded as learning?

79   -[IMPROVING ECOLOGICAL VALIDITY OF PARADIGM] A secondary aim was to

80   begin to address possible concerns of ecological validity of prior work. While no speech stimuli is

81   ever ideal, previous work on which the current study is based did have limitations in one or two

82   aspects:the artificiality of the stimuli or the artificiality of the distributions. For e.g. (Clayards et

83   al., 2008a) and (Kleinschmidt & Jaeger, 2016) made use of synthesised stimuli that were robotic

84   or did not sound human-like. The second way that those studies were limited was that the

85   exposure distributions of the linguistic categories had identical variances (see also Theodore &

86   Monto, 2019) unlike what is found in production data where the variance of the voiceless

87   categories are typically wider than that of the voiced category (Chodroff & Wilson, 2017). We

88   take modest steps to begin to improve the ecological validity of this study while balancing the

89   need for control through lab experiments by employing more natural sounding stimuli as well as

90   by setting the variances of our exposure distributions to better reflect empirical data on

91   production (see section x.xx. of SI).

1.1   Methods

1.1.1   Participants

94   Participants were recruited over the Prolific platform and experiment data (but not participant

95   profile data) were collected, stored, and via proliferate ((**schuster?**)). They were paid $8.00 each

96   (for a targeted remuneration of $9.60/hour). The experiment was visible to participants following

97   a selection of Prolific's available pre-screening criteria. Participants had to (1) have US

98   nationality, (2) report to only know English, and (3) had not previously participated in any

99   experiment from our lab on Prolific.

100   126 L1 US English listeners (male = 60, female = 59, NA = 3; mean age = 38 years; SD

101   age = 12 years) completed the experiment. Due to data transfer errors 4 participants' data were

102   not stored and therefore not included in this analysis. To be eligible, participants had to confirm

103   that they (1) spent at least the first 10 years of their life in the US speaking only English, (2)

104   were in a quiet place and free from distractions, and (3) wore in-ear or over-the-ears headphones

105   that cost at least $15.

1.1.2 Materials

We recorded multiple tokens of four minimal word pairs ("dill"/"till", "dim"/"tim", "din"/"tin", and "dip"/"tip") from a 23-year-old, female L1 US English talker from New Hampshire, judged to have a "general American" accent. These recordings were used to create four natural-sounding minimal pair VOT continua (dill-till, dip-tip, din-tin, and dip-tip) using a Praat script (Winn, 2020). In addition to the critical minimal pair continua we also recorded three words that did not did not contain any stop consonant sounds ("flare", "share", and "rare"). These word recordings were used as catch trials. Stimulus intensity was set to 70 dB sound pressure level for all recordings. The full procedure is described in the supplementary information (SI, **??**).

We also set the F0 at vowel onset to follow the speaker's natural correlation which was estimated through a linear regression analysis of all the recorded speech tokens. We did this so that we could determine the approximate corresponding f0 values at each VOT value along the continua as predicted by this talker's VOT. The duration of the vowel was set to follow the natural trade-off relation with VOT reported in Allen and Miller (1999). This approach resulted in continuum steps that sound highly natural (unlike the robotic-sounding stimuli employed in Clayards et al., 2008a; Kleinschmidt & Jaeger, 2016). All stimuli are available as part of the OSF repository for this article.

Prior to creating the three exposure conditions of the experiment, we ran a norming experiment to test US-L1 listeners' perception of our stimuli and to determine a baseline categorisation boundary for this talker. While it is normal and acceptable practice to set the baseline by taking population estimates of mean values from past studies on stops, we reasoned that such estimates were highly variable and therefore aimed to obtained a more accurate estimation of how L1-US English listeners perceived the speech of our talker. To anticipate the outcome, we eventually discovered that the classification boundary from norming underestimated the boundary fitted to our participants' classification in the initial test block. This placed our baseline and baseline +10ms shift exposure conditions slightly leftwards of participants' initial perceptual boundary. This finding, however does not impinge on the conclusions drawn from this study []

134   The other purpose of the norming experiment was to detect possible anomalous features
135 present in our stimuli (for e.g. if it would elicit unusual categorisation behaviour or whether
136 certain minimal-pairs had an exaggerated effect on categorisation). For the norming experiment
137 the VOT continua employed 24 VOT steps ranging from -100ms VOT to +130ms (-100, -50, -10,
138 5 15, 20, 25, 30, 35, 40, 45, 50, 55, 60, 65, 70, 75, 80, 85, 90, 100, 110, 120, 130). VOT tokens in
139 the lower and upper ends were distributed over larger increments because stimuli in those ranges
140 were expected to elicit floor and ceiling effects, respectively. We found VOT to have the expected
141 effect on the proportion of "t"-responses, i.e. higher VOTs elicited greater "t"-responses and that
142 the word-pairs did not differ substantially from each other. The results and analysis of the
143 norming experiment are reported in full in section **??**.

144   A subset of the materials were used to generate the three exposure conditions; in particular
145 three continua of the minimal pairs, dill-till, din-tin, and dip-tip. The dim-tim continuum was
146 omitted in order to keep the pairs as distinct as possible.

147   We employed a multi-block exposure-test design 1 which enabled the assessment of listener
148 perception before informative exposure as well as incrementally at intervals during informative
149 exposure (after every 48 exposure trials). To have a comparable test between blocks and across
150 conditions, test blocks were made up of a uniform distribution of 12 VOT stimuli (-5, 5, 15, 25,
151 30, 35, 40, 45, 50, 55, 65, 70), identical across test blocks and between conditions. Each of the test
152 tokens were presented once at random. The test blocks were kept short to minimise distortion of
153 the intended distribution to be presented by the end of the exposure phase. After the final
154 exposure block we tripled the number of test blocks to increase the statistical power to detect
155 exposure induced behavioural changes.

156   The conditions were created by first generating a baseline distribution and then shifting the
157 baseline by +10ms and by +40ms towards the right of the VOT continuum to create the
158 remaining two conditions.

159   To construct the baseline exposure distribution we first computed the point of subjective
160 equality (PSE) from the perceptual component of the fitted psychometric function of listener
161 responses in the norming experiment. The PSE corresponds to the VOT duration that was
162 perceived as most ambiguous across all participants during norming (i.e. the stimulus that on
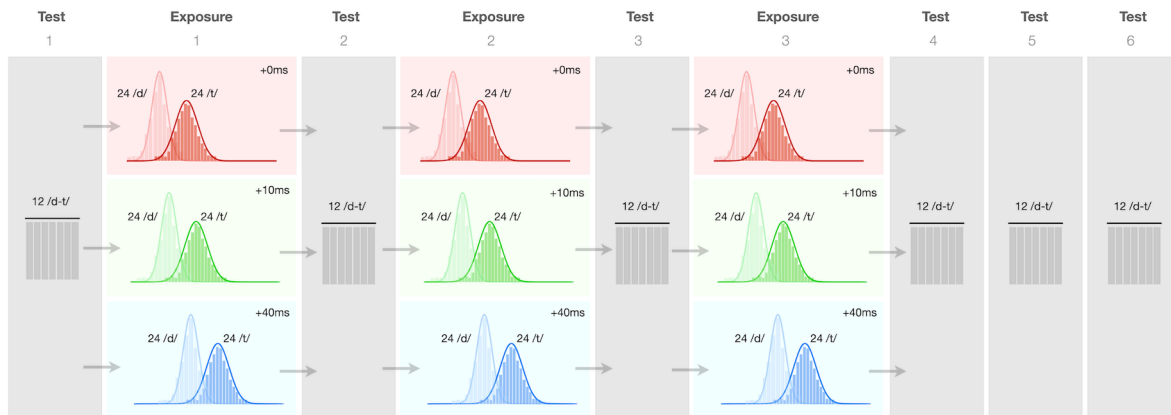
Figure 1. Experiment 2 multi-block design. Test blocks in grey comprised identical stimuli within and between conditions

163   average, elicited equal chance of being categorised as /d/ or /t/) thus marking the categorical

164   boundary. From a distributional perspective the PSE is where the likelihoods of both categories

165   intersect and have equal probability density (we assumed Gaussian distributions and equal prior

166   probability for each category). To limit the infinite combinations of category likelihoods that

167   could intersect at this value, we set the variances of the /d/ (80ms) and /t/ (270ms categories

168   based on parameter estimates (X. Xie, Jaeger, and Kurumada (2022)) obtained from the

169   production database of word-initial stops in Chodroff and Wilson (2017). To each variance value

170   we added 80ms following (Kronrod, Coppess, and Feldman (2016)) to account for variability due

171   to perceptual noise since these likelihoods were estimated from perceptual data. We took an

172   additional degree of freedom of setting the *distance between the means* of the categories at 46ms;

173   this too was based on the mean for /d/ and /t/ estimated from the production database. The

174   means of both categories were then obtained through a grid-search process to find the likelihood

175   distributions that crossed at 25ms VOT (see XX of SI for further detail on this procedure).

176   The distributional make up was determined through a process of sampling tokens from a

177   discretised normal distribution with values rounded to the nearest multiple of 5 integer (available

178   through the `extraDistr` package in R). For each exposure block 8 VOT tokens per minimal word

179   pair were sampled from discrete normal distributions of each category of the baseline condition,

180   giving 24 /d/ and 24 /t/ items (48 critical trials) per block. The sampled distributions of VOT

181   tokens were increased by a margin of +10ms and +40 ms to create the remaining two conditions

182 (figure 2). Additionally, each exposure block contained 2 instances of 3 catch items, giving 6 catch

183 trials per block. These catch trials were recordings of the words, "flare", "share", or "rare",

184 presented in the same manner as critical trials but clearly distinguishable. They served as a check

185 on participant attention during the experiment. Three variants of each condition list were created

186 so that exposure blocks followed a latin-square order.

187   Lastly, half of the exposure trials were randomly assigned as labelled trials. In labelled

188 trials, participants receive clear information of the word's category as both orthographic options

189 will always begin with the intended sound. For example if a trial was intended to be "dill" then

190 the two image options will either be "dill" and "dip" or "dill" and "din". Test trials were always
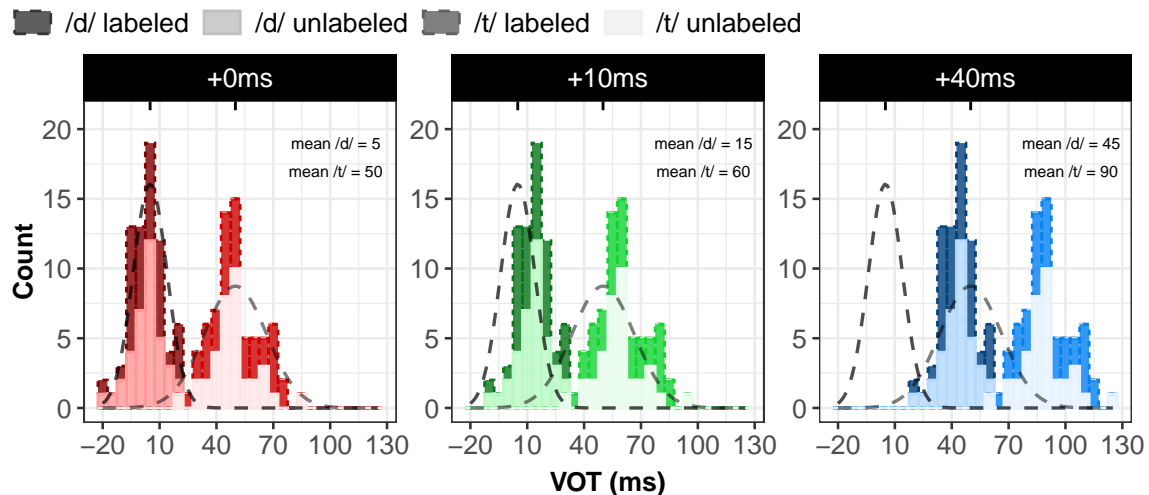
191 *unlabelled.*

Figure 2. Histogram of all 144 exposure tokens presented over the three exposure blocks. VOT
items were counter balanced over

1.1.3 Procedure

193 The code for the experiment is available as part of the OSF repository for this article. A live

194 version is available at (https://www.hlp.rochester.edu/FILLIN-FULL-URL). The first page of

195 the experiment informed participants of their rights and the requirements for the experiment:

196 that they had to be native listeners of English, wear headphones for the entire duration of the

197 experiment, and be in a quiet room without distractions. Participants had to pass a headphone

test, and were asked to keep the volume unchanged throughout the experiment. Participants could only advance to the start of the experiment by acknowledging each requirement and consenting to the guidelines of the Research Subjects Review Board of the University of Rochester.

On the next page, participants were informed about the task for the remainder of the experiment. They were informed that they would hear a female talker speak a single word on each trial, and had to select which word they heard. They were also informed that they needed to click a green button that would be displayed during each trial when it "lights up" in order to hear the recording of the speaker saying the word. Participants were instructed to listen carefully and answer as quickly and as accurately as possible. They were also alerted to the fact that the recordings were subtly different and therefore may sound repetitive. This was done to encourage their full attention.

Each trial started with a dark-shaded green fixation dot being displayed. At 500ms from trial onset, two minimal pair words appeared on the screen, as shown in Figure **??**. At 1000ms from trial onset, the fixation dot would turn bright green and participants had to click on the dot to play the recording. Participants responded by clicking on the word they heard and the next trial would begin. The placement of the word presentations were counter-balanced across participants.

Participants underwent 234 trials which included 6 catch trials in each exposure block (18 in total). Since these recordings were easily distinguishable, they served as a check on participant attention throughout the experiment. Catch trials were distributed randomly throughout the experiment with the constraint that no more than two catch trials would occur in a row. Participants were given the opportunity to take breaks after every 60 trials during exposure blocks. Participants took an average of 17 minutes (SD = 9) to complete the 234 trials, after which they answered a short survey about the experiment.
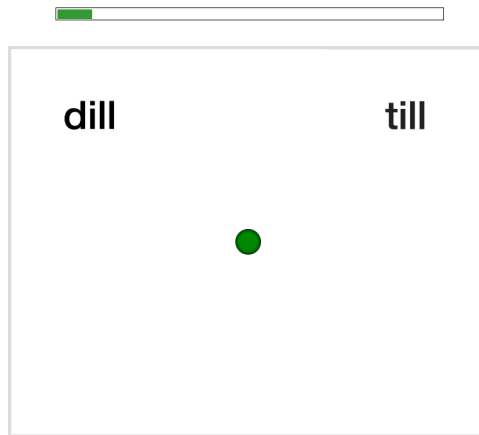
Figure 3. Example trial display. The words were displayed 500ms after trial onset. The green button would turn bright green signalling participants to click on the dot to play the recording.

1.1.4 Exclusions

We excluded from analysis participants who committed more than 3 errors out of the 18 catch trials (<83% accuracy, N = 1), participants who committed more than 4 errors out of the 72 labelled trials (<94% accuracy, N = 0), participants with an average reaction time (RT) more than three standard deviations from the mean of the by-participant means (N = 0), and participants who reported not to have used headphones (N = 0) or not to be native (L1) speakers of US English (N = 0).

In addition, participants' categorization during the early phase of the experiment were scrutinised for their slope orientation and their proportion of "t"-responses at the least ambiguous locations of the VOT continuum. The early phase of the experiment was defined as the first 36 trials and the least ambiguous locations were defined as -20ms below the empirical mean of the /d/ category and +20ms above the empirical mean of the /t/ category. These means were obtained from the production data estimates by X. Xie et al. (2022).

1.1.5 Analysis approach

1.2 Results

1.3   Regression analysis

The regression analysis addresses several questions:

1. Do listeners change their categorization behaviour in the direction predicted by their respe

2. At what stage in the experiment did the behavioural change first emerge?

3. Are the shifts in categorisation behaviour proportional to the differences between the expos

4. Do the differences between exposure conditions diminish with repeated testing and without i

We fit a Bayesian mixed-effects psychometric model to participants' categorization responses on critical test trials (e.g., **prins2011?**). We are primarily interested in the changes in categorization behaviour between test blocks which are presumed to be a consequence of the input from preceding exposure blocks however we fit a separate regression model for exposure in order to visualise participant behaviour during exposure.

The psychometric model is essentially an extension of mixed-effects logistic regression that also takes into account attentional lapses. Ignoring attentional lapses–while commonplace in research on speech perception (incl. our own work, but see Clayards, Tanenhaus, Aslin, & Jacobs, 2008b; Kleinschmidt & Jaeger, 2016)—can lead to biased estimates of categorization boundaries (e.g., Wichmann & Hill, 2001). The mixed-effects psychometric model describes the probability of "t"-responses as a weighted mixture of a lapsing-model and a perceptual model. The lapsing model is a mixed-effects logistic regression (Jaeger, 2008) that predicts participant responses that are made independent of the stimulus—for example, responses that result from attentional lapses. These responses are independent of the stimulus, and depend only on participants' response bias. The perceptual model is a mixed-effects logistic regression that predicts all other responses, and captures stimulus-dependent aspects of participants' responses. The relative weight of the two models is determined by the lapse rate, which is described by a third mixed-effects logistic regression.

We fit the model using the package `brms` (Bürkner, 2017) in R (R Core Team, 2021a; RStudio Team, 2020). Following previous work from our lab (Hörberg & Jaeger, 2021; X. Xie et al., 2021), we used weakly regularizing priors to facilitate model convergence. For fixed effect parameters, we standardized continuous predictors (VOT) by dividing through twice their

standard deviation (Gelman, 2008), and used Student priors centered around zero with a scale of 2.5 units (following Gelman, Jakulin, Pittau, & Su, 2008) and 3 degrees of freedom. For random effect standard deviations, we used a Cauchy prior with location 0 and scale 2, and for random effect correlations, we used an uninformative LKJ-Correlation prior with its only parameter set to 1, describing a uniform prior over correlation matrices (**Lewandowski2009?**). Four chains with 2000 warm-up samples and 2000 posterior samples each were fit. No divergent transitions after warm-up were observed, and all $\hat{R}$ were close to 1.

To analyse the incremental effects of exposure condition on the proportion of "t"-responses at test, the perceptual model contained exposure condition (backward difference coded, comparing the +10ms against the +0ms shift condition, and the +40ms against the +10ms shift condition), test block (backward difference coded from the first to last test block), VOT (Gelman scaled), and their full factorial interaction. For the perceptual model, "t"-responses were regressed on the three-way interaction of VOT, condition, and block. Random effects were modelled with varying intercepts and slopes by participant and varying intercepts and slopes by minimal pair item. We assumed a uniform bias in participant responses, that is, on lapsing trials participants would respond "t" half the time and fitted a population-level intercept for the lapse rate. Random effects for the lapsing model and lapse rates were not fitted to reduce the number of parameters and to facilitate model convergence.

Figure @**??**fig:plot-fit-intercept-slope-PSE) summarizes participants' fitted categorization functions across the different test blocks. Of note is the average categorization functions of the respective conditions before exposure informative exposure. As depicted in the first panel, the average categorization functions converge on the same boundary or PSE (45ms, 95% QI = 36ms – 55ms) which suggests that the three exposure groups largely had similar expectations about the cue distribution corresponding to /d/ and /t/ for this type of talker.

1.4   Description of the overall pattern of results (main effects)

- The overall lapse rate was negligible ($\hat{\beta}$ = NA %, 95%-CI: NA to NA%; Bayes factor: Inf 90%-CI : -5.39 to -4.24) indicating that participants were paying attention in the majority of trials.

- There was a main effect of VOT ($\hat{\beta} = 15.7$ 95%-CI: 12.5 to 19.2; Bayes factor: 7,999 90%-CI : 13.15 to 18.4): participants were more likely to respond "t" as VOT increased.

- Condition had a main effect on responses such that with larger shifts away from the baseline, participants responded with fewer "t"s.

- Comparing the +10ms condition with the baseline condition across all blocks: there was a reduction in log-odds of responding "t" in the +10ms condition compared to the baseline condition ($\hat{\beta} = -1$ 95%-CI: -2.8 to 0.7; Bayes factor: 9.24 90%-CI : -2.24 to 0.3).

- Comparing the +40ms against the +10ms condition across all blocks: there was a reduction in log-odds of responding "t" in the +40ms condition compared to the +10ms condition ($\hat{\beta} = -2.4$ 95%-CI: -3.8 to -1.1; Bayes factor: 443.44 90%-CI : -3.54 to -1.36).

- Tellingly, the reduction in log-odds was larger in the +40 vs +10ms comparison, reflecting the larger magnitude of shift from the baseline (Bayes factor: 9.28 90%-CI : -3.36 to 0.44).

1.4.1   Interactions

The interactions provide between block comparisons of the differences between conditions. We focus on the first 4 test blocks as they were interspersed with exposure. In order to examine the effects of exposure condition on behaviour within block, and how each condition changed by block (simple effects of condition and block) we fitted 2 nested models that embed condition within block, and block within condition. We report the interactions in conjunction with the simple effects.

- Comparing the change in differences between +10ms and baseline between blocks: we see an overall reduction in the log-odds of responding "t" between test blocks 1 and 4 however almost all that reduction took place between test blocks 1 and 2 ($\hat{\beta} = -1.4$ 95%-CI: -3.5 to 0.6; Bayes factor: 13.52 90%-CI : -3.06 to 0.2). Between test blocks 2 and 4, differences in behaviour between the two groups did not change significantly in spite of increased input from the exposure blocks.

- Comparing the change in differences between +40ms and +10ms between blocks: -There was a consistent reduction in log-offs of responding "t" from blocks 1 through 4, indicating an incremental shift in categorisation towards the right as participants received more input.

321   The biggest change was observed between test block 1 and 2 ($\hat{\beta}$ = -2.1 95%-CI: -4.4 to 0.2;

322   Bayes factor: 27.78 90%-CI : -3.89 to -0.23).

323   – The difference between condition +40 and +10 continued to widen after the second

324   exposure block, ($\hat{\beta}$ = -1.8 95%-CI: -4.1 to 0.5; Bayes factor: 19.15 90%-CI : -3.69 to 0)

325   but not much incremental shift was observed in the 4th test block in spite of full

326   exposure to the 144 trials at this stage ($\hat{\beta}$ = -0.5 95%-CI: -3.3 to 2.1; Bayes factor: 1.69

327   90%-CI : -2.63 to 1.62)

328 `## Warning in tidy.brmsfit(fit_mix_test_nested_block, effects = "fixed"): some parameter names`

329 `## Warning in tidy.brmsfit(fit_mix_test_nested_condition, effects = "fixed"): some parameter na`

Table 1
Comparing interactions of block and condition

Hypothesis	Estimate	Est Error	CI Lower	CI Upper	Evid Ratio	Post Prob
10 vs baseline in test 2 > test 1	-1.41	1.1	-3.1	0.20	13.52	0.93
10 vs baseline in test 3 > test 2	0.83	1.3	-1.1	2.78	0.25	0.20
10 vs baseline in test 4 > test 3	0.01	1.3	-1.8	1.89	1.02	0.50
40 vs 10 in test 2 > test 1	-2.06	1.2	-3.9	-0.23	27.78	0.96
40 vs 10 in test 3 > test 2	-1.81	1.2	-3.7	0.00	19.15	0.95
40 vs 10 in test 4 > test 3	-0.47	1.6	-2.6	1.62	1.70	0.63

Table 2

Comparing conditions in test blocks 1 to 4

Hypothesis	Estimate	Est Error	CI Lower	CI Upper	Evid Ratio	Post Prob
10 vs baseline > diff btwn 40 vs 10 in test 1	-0.60	1.8	-3.4	2.16	0.55	0.35
shift in 40 vs 10 > 10 vs baseline in test 2	0.04	2.1	-3.3	3.55	0.97	0.49
shift in 40 vs 10 > 10 vs baseline in test 3	-2.43	1.6	-5.0	0.04	18.30	0.95
shift in 40 vs 10 > 10 vs baseline in test 4	-3.01	1.9	-6.1	-0.07	20.90	0.95
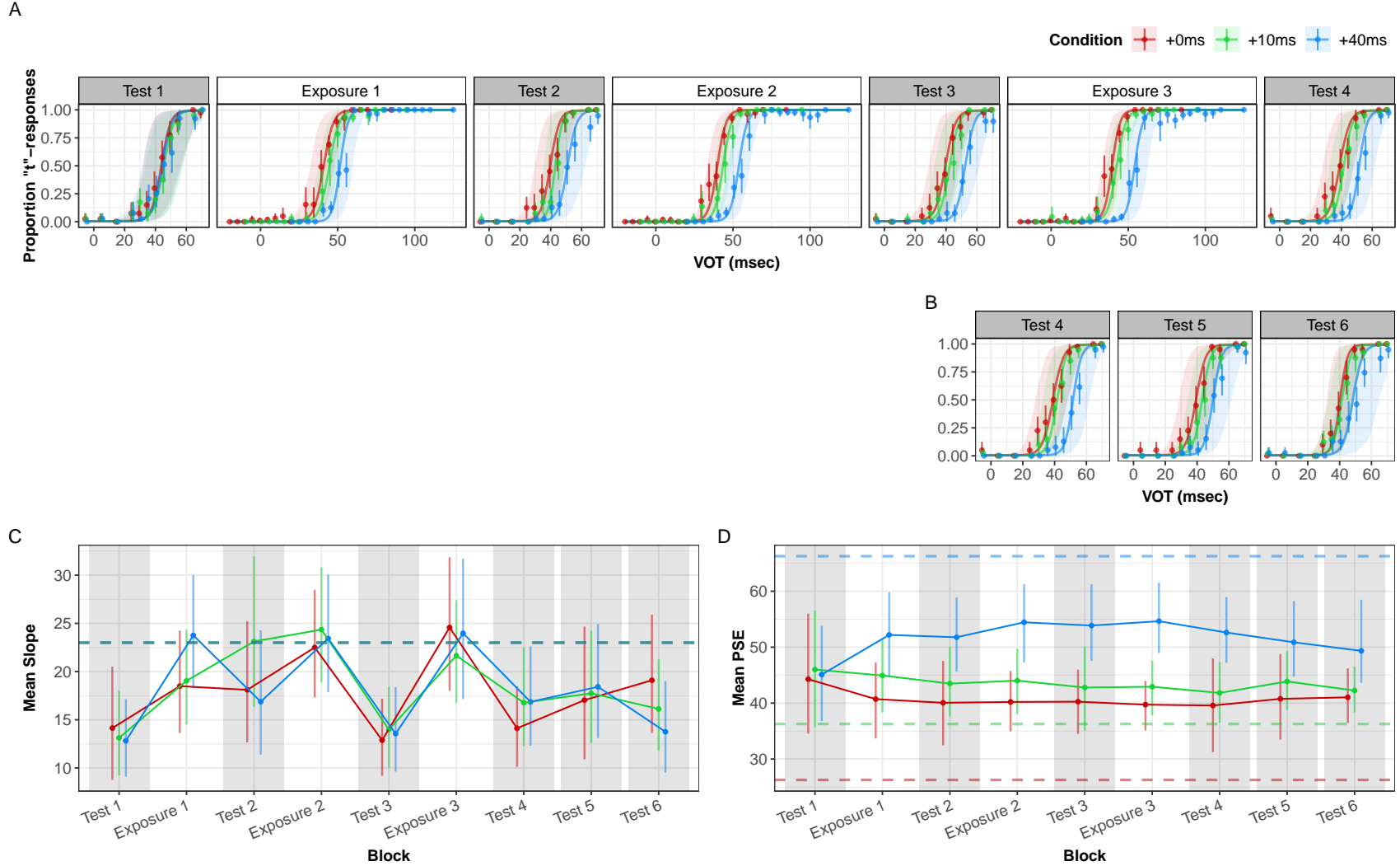
Figure 4. **A:** Fitted lapse-rate corrected psychometric plots by exposure condition (all exposure and first 4 test blocks); point ranges indicate the mean proportion of "t"-responses and their 95% bootstrapped CI. **B:** Change in final three test blocks in the absence of more input. **C & D:** Changes in intercepts, slopes and categorisation boundary (represented by the point-of-subjective-equality (PSE)) by block. Summary is of 8000 draws from the maximum *a posteriori* estimate. Points represent the mean of posterior draws and line ranges are the 95% quantile interval of all draws. Dashed lines show the predicted intercepts, slopes and PSEs by the ideal observers of the respective conditions that have perfectly learned the exposure distributions.
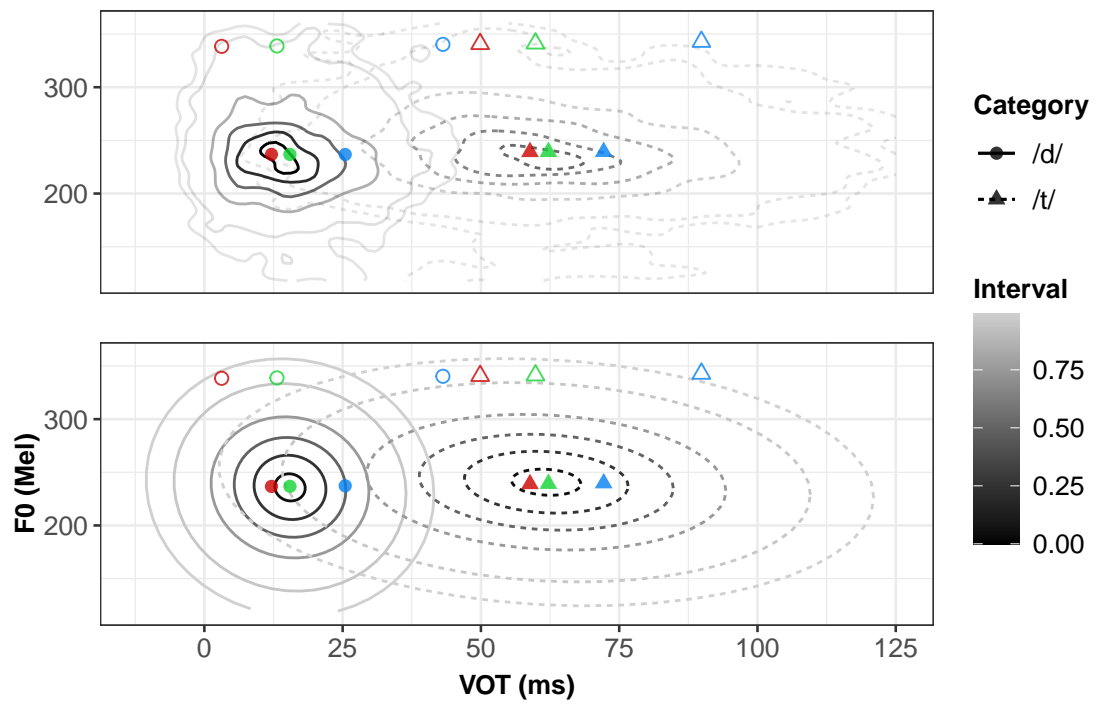
Figure 5

330   All data and code for this article can be downloaded fromhttps://osf.io/q7gjp/. This article
331 is written in R markdown, allowing readers to replicate our analyses with the press of a button
332 using freely available software (R, R Core Team, 2021a; RStudio Team, 2020), while changing any
333 of the parameters of our models. Readers can revisit any of the assumptions we make—for
334 example, by substituting alternative models of linguistic representations. The supplementary
335 information (SI, §1) lists the software/libraries required to compile this document. Beyond our
336 immediate goals here, we hope that this can be helpful to researchers who are interested in
337 developing more informative experimental designs, and to facilitate the interpretation of existing
338 results (see also Tan, Xie, & Jaeger, 2021).

339 2   General discussion

340 2.1   Methodological advances that can move the field forward

341 An example of a subsection.

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544 ## Supplementary information

545 Both the main text and these supplementary information (SI) are derived from the same R

546 markdown document available via OSF. It is best viewed using Acrobat Reader. Some links and

547 animations might not work in other PDF viewers.

548 ## §1   Required software

549 The document was compiled using `knitr` (Y. Xie, 2021) in RStudio with R:

```
550 ##                    _
551 ## platform       x86_64-apple-darwin17.0
552 ## arch           x86_64
553 ## os             darwin17.0
554 ## system         x86_64, darwin17.0
555 ## status
556 ## major          4
557 ## minor          1.3
558 ## year           2022
559 ## month          03
560 ## day            10
561 ## svn rev        81868
562 ## language       R
563 ## version.string R version 4.1.3 (2022-03-10)
564 ## nickname       One Push-Up
```

565 You will also need to download the IPA font SIL Doulos and a Latex environment like (e.g.,

566 MacTex or the R library `tinytex`).

567 We used the following R packages to create this document: R (Version 4.1.3; R Core Team,

568 2021b) and the R-packages *}broom* [@}R-broom], *assertthat* (Version 0.2.1; Wickham, 2019a),

569 *brms* (Version 2.19.0; Bürkner, 2017, 2018, 2021), *broom.mixed* (Version 0.2.9.4; Bolker &

Robinson, 2022), *cowplot* (Version 1.1.1; Wilke, 2020), *curl* (Version 5.0.0; Ooms, 2022), *data.table* (Version 1.14.8; Dowle & Srinivasan, 2021), *diptest* (Version 0.76.0; Maechler, 2021), *dplyr* (Version 1.1.2; Wickham, François, Henry, & Müller, 2021), *forcats* (Version 1.0.0; Wickham, 2021a), *gganimate* (Version 1.0.8; Pedersen & Robinson, 2020), *ggdist* (Version 3.3.0; Kay, 2022a), *ggforce* (Version 0.4.1; Pedersen, 2022a), *ggnewscale* (Version 0.4.8; Campitelli, 2022), *ggplot2* (Version 3.4.2; Wickham, 2016), *ggpubr* (Version 0.6.0; Kassambara, 2020), *ggrepel* (Version 0.9.3; Slowikowski, 2021), *ggstance* (Version 0.3.6; Henry, Wickham, & Chang, 2020), *gt* (Version 0.9.0; Iannone et al., 2023), *kableExtra* (Version 1.3.4; Zhu, 2021), *knitr* (Version 1.42; Y. Xie, 2015), *LaplacesDemon* (Version 16.1.6; Statisticat & LLC., 2021), *latexdiffr* (Version 0.1.0; Hugh-Jones, 2021), *linguisticsdown* (Version 1.2.0; Liao, 2019), *lme4* (Version 1.1.33; Bates, Mächler, Bolker, & Walker, 2015), *lmerTest* (Version 3.1.3; Kuznetsova, Brockhoff, & Christensen, 2017), *lubridate* (Version 1.9.2; Grolemund & Wickham, 2011), *magick* (Version 2.7.4; Ooms, 2021), *magrittr* (Version 2.0.3; Bache & Wickham, 2020), *MASS* (Version 7.3.60; Venables & Ripley, 2002), *Matrix* (Version 1.5.1; Bates & Maechler, 2021), *modelr* (Version 0.1.11; Wickham, 2020), *pander* (Version 0.6.5; Daróczi & Tsegelskyi, 2022), *papaja* (Version 0.1.1.9,001; Aust & Barth, 2020), *patchwork* (Version 1.1.2; Pedersen, 2022b), *phonR* (Version 1.0.7; McCloy, 2016), *plotly* (Version 4.10.1; Sievert, 2020), *posterior* (Version 1.4.1; Vehtari, Gelman, Simpson, Carpenter, & Bürkner, 2021), *processx* (Version 3.8.1; Csárdi & Chang, 2021), *purrr* (Version 1.0.1; Henry & Wickham, 2020), *RColorBrewer* (Version 1.1.3; Neuwirth, 2022), *Rcpp* (Eddelbuettel & Balamuta, 2018; Version 1.0.10; Eddelbuettel & François, 2011), *readr* (Version 2.1.4; Wickham, Hester, & Bryan, 2021), *rlang* (Version 1.1.1; Henry & Wickham, 2021), *rsample* (Version 1.1.1; Frick et al., 2022), *scales* (Version 1.2.1; Wickham & Seidel, 2022), *sjPlot* (Version 2.8.14; Lüdecke, 2023), *stringr* (Version 1.5.0; Wickham, 2019b), *tibble* (Version 3.2.1; Müller & Wickham, 2021), *tidybayes* (Version 3.0.4; Kay, 2022b), *tidyr* (Version 1.3.0; Wickham, 2021b), *tidyverse* (Version 2.0.0; Wickham et al., 2019), *tinylabels* (Version 0.2.3; Barth, 2022), *tufte* (Version 0.12; Y. Xie & Allaire, 2022), and *webshot* (Version 0.5.4; Chang, 2022). If opened in RStudio, the top of the R markdown document should alert you to any libraries you will need to download, if you have not already installed them. The full session information is provided at the end of this document.

§2 Overview

§2.1 Overview of data organisation

§3 Stimuli generation for perception experiments

§3.1 Recording of audio stimuli

An L1-US English female talker originally from New Hampshire was recruited for recording of the stimuli. She was recorded at the Human Language Processing lab at the Brain & Cognitive Sciences Department, University of Rochester with the help of research assistant (also an L1-US English speaker). She was 23 years old at the time of recording and was judged by the research assistant to have a generic US American accent known as "general American".

Four /d-t/ minimal pairs (dill-till, din-tin, dim-tim, dip-tip) were recorded together with 20 filler words. These fillers were made up of 10 minimal or near minimal pairs with different sounds at onset. The word pairs were separated into two lists so that they would appear in separate blocks during recording. Each critical pair was repeated 8 times while the filler pairs were repeated 5 times. Word presentation was delivered with PsychoPy (**Peirce2019?**) and the presentation was controlled by the researcher from a computer located outside the recording room. The order of each block was randomised such that target words never appeared consecutively. The talker was instructed to speak clearly and confidently, and to maintain a consistent distance from the microphone.

§3.2 Annotation of audio stimuli

All critical pairs of the talker's recordings were annotated. Durational, measurements of voicing lead, VOT, and vowel were taken in addition to the mean F0 of the first 25% of the vowel duration. Annotations were made with a combination of listening to the audio file and inspection of the waveform and spectrogram. The annotation boundaries were made according to the following principles:

- pre-voicing (voicing during closure) -**start:** the first sign of periodicity in the waveform

623   before closure release. -**End:** the point of closure release

624   • VOT -**start:** the point of closure release. -**End:** the beginning of clearly defined periodicity
625   in the waveform and at the appearance of low frequency energy in the spectrogram.

626   • Vowel -**start:** the beginning of clearly defined periodicity in the waveform and at the
627   appearance of low frequency energy in the spectrogram. -**End:** if before a stop, when
628   periodicity becomes irregular or at closure onset; if before a lateral, when formant transition
629   approaches steady state; if before a nasal, when formants show a step-wise shift and when
630   intensity shows a steep decline.

631   • F0 at vowel onset -the average pitch measurement estimated over the first 25% of the total
632   vowel duration.

633   [INSERT EXAMPLE IMAGES]

634   ## §3.3   Synthesis of audio stimuli

635   The stimuli was created using the "progressive cutback and replacement method" by (Winn,
636   2020) implemented in Praat (Boersma & Weenink, 2022). This automates and greatly simplifies
637   the process for generating highly natural sounding stimuli. Users of the script need only specify
638   certain parameters to produce desired stimuli. Stimuli with pre-voicing were created separately
639   from stimuli with positive VOT. This was because the script was not coded to automate the
640   creation of tokens with pre-voicing that are natural sounding [1]. As such, the pre-voicing stimuli
641   were created by prepending pre-voicing generated from naturally produced tokens (described
642   below) that were edited with a separate process.

643   ## §3.4   Positive VOT tokens

644   For each minimal pair a continuum of 31 tokens was generated between 0ms and 150ms with a
645   step-size of 5ms. A token of the voiced category from each pair was selected to be the base sound

---

[1] it can however, produce pre-voicing sufficiently well for demonstration purposes, see video demo at
https://www.youtube.com/watch?v=-QaQCsyKQyo

file to make the continuum. All four minimal pair continua had an identical aspiration sound which was excised from one of the voiceless tokens produced by the talker.

While the main manipulation of the recordings was done on VOT we set the fundamental frequency (F0) to covary with VOT according to the natural correlation exhibited by our talker. The F0 values were predicted by regressing the talker's F0 measurements on VOT. Target F0 values for each token were then generated by setting the predicted F0 values of the end-point VOT tokens (0ms and 150ms) in the Praat script.

The vowel cut-back ratio was set at 0.33 which translates into a third of a ms vowel reduction for every 1ms of VOT. This ratio followed the estimated vowel duration-VOT trade-off for dip-tip minimal pair tokens reported in (**allenMiller?**). The maximum allowed vowel cut-back was 0.5ms to avoid the short vowel in **dip** becoming too short. Lastly, the rate of increase for aspiration intensity was kept at the default settings of the script.

§3.5   Pre-voicing tokens

Pre-voicing in 5ms increments were generated from a a clear pre-voicing waveform excised from a voiced token produced by the talker. To achieve a desired duration a duration factor is first computed and then converted with the "lengthen (overlap-add)" function in Praat. For example, if the desired amount of prevoicing was 50ms then the duration factor would be 50ms/length of the original pre-voicing sample. Each pre-voicing step is then prepended to a token with 0ms VOT. Each of these 0ms tokens was generated with Winn (2020) Praat script by manually entering the expected F0 value for a given pre-voicing duration based on the predictions of the linear model. No vowel-cut back was implemented for pre-voiced tokens.

All the synthesised stimuli were subsequently annotated for pre-voicing, VOT, vowel duration and F0 at the first 5ms from vowel onset. This F0 measurement was made in order to align the data with the production database that we use for ideal observer analysis. Each item's F0 in relation to VOT is plotted in figure X.

```
##
## Call:
## lm(formula = f0_5ms_into_vowel ~ 1 + VOT, data = d)
```

```
674  ##
675  ## Coefficients:
676  ## (Intercept)          VOT
677  ##     245.4697       0.0383
```
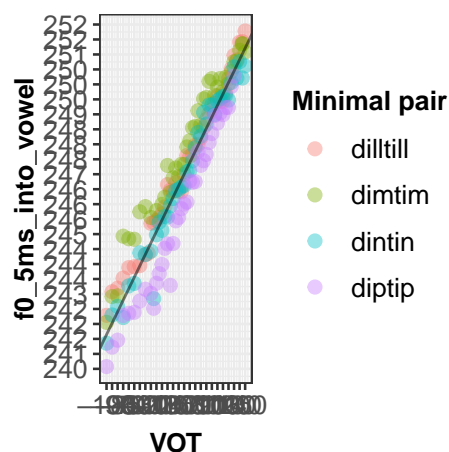

Figure 6

674. **§3.5.1 Making exposure conditions**

§4 Web-based experiment design procedure

§4.1 Norming experiment: Listener's expectations prior to informative exposure

The norming experiment investigates native (L1) US English listeners' categorization of word-initial stop voicing by an unfamiliar female L1 US English talker, prior to more informative exposure. Specifically, listeners heard isolated recordings from a /d/-/t/ continuum, and had to respond which word they heard (e.g., "din" or "tin"). The recordings varied in voice onset time (VOT), the primary phonetic cue to word-initial stop voicing in L1 US English, as well as correlated secondary cues (f0 and rhyme duration). Critically, exposure was relatively uninformative about the talker's use of the phonetic cues in that all phonetic realizations occurred equally often.
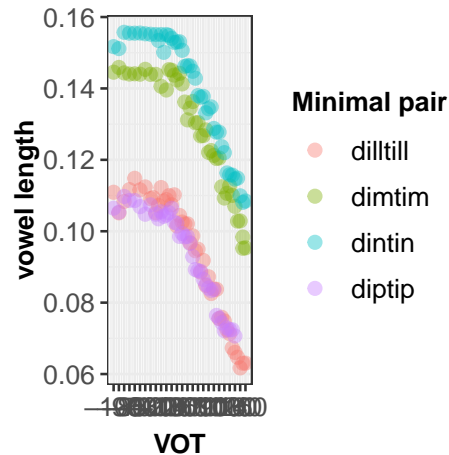
Figure 7

690 The primary goal of norming was methodological. We used the norming experiment to test

691 basic assumptions about the paradigm and stimuli we employ in this study. We obtain estimates

692 of the category boundary between /d/ and /t/ *for the specific stimuli used in Experiment 2*, as

693 perceived by *the type of listeners we seek to recruit for the main experiment*. We also test whether

694 prolonged testing across the phonetic continuum changes listeners' categorization behavior.

695 Previous work has found that prolonged testing on uniform distributions can reduce the effects of

696 previous exposure (Liu & Jaeger, 2018a; e.g., **mitterer2011?**), at least in listeners of the age

697 group we recruit from (Scharenborg & Janse, 2013). However, these studies employed only a

698 small number of 5-7 perceptually highly ambiguous stimuli, each repeated many times. In the

699 norming experiment, we employ a much larger set of stimuli that span the entire continuum from

700 very clear /d/s to very clear /t/s, each presented only twice. If prolonged testing changes

701 listeners' responses, this has to be taken into account in the design of the main.

§4.2 Methods

§4.2.1 Participants

704 Participants were recruited over Amazon's Mechanical Turk platform, and paid \$2.50 each (for a

705 targeted remuneration of \$6/hour). The experiment was only visible to Mechanical Turk

706 participants who (1) had an IP address in the United States, (2) had an approval rating of 95%

707 based on at least 50 previous assignments, and (3) had not previously participated in any

708 experiment on stop voicing from our lab.

709   24 L1 US English listeners (female = 9; mean age = 36.2 years; SD age = 9.2 years)

710 completed the experiment. To be eligible, participants had to confirm that they (1) spent at least

711 the first 10 years of their life in the US speaking only English, (2) were in a quiet place, and (3)

712 wore in-ear or over-the-ears headphones that cost at least $15.

713 **§4.2.2   Materials**

714 The VOT continua ranged from -100ms VOT to +130ms VOT in 5ms steps. Experiment 1

715 employs 24 of these steps (-100, -50, -10, 5 15, 20, 25, 30, 35, 40, 45, 50, 55, 60, 65, 70, 75, 80, 85,

716 90, 100, 110, 120, 130). VOT tokens in the lower and upper ends were distributed over larger

717 increments because stimuli in those ranges were expected to elicit floor and ceiling effects,

718 respectively.

719   We further set the F0 at vowel onset to follow the speaker's natural correlation which was

720 estimated through a linear regression analysis of all the recorded speech tokens. We did this so

721 that we could determine the approximate corresponding f0 values at each VOT value along the

722 continua as predicted by this talker's VOT. The duration of the vowel was set to follow the natural

723 trade-off relation with VOT reported in Allen and Miller (1999). This approach closely resembles

724 that taken in Theodore and Monto (2019), and resulted in continuum steps that sound highly

725 natural (unlike the robotic-sounding stimuli employed in Clayards et al., 2008a; Kleinschmidt &

726 Jaeger, 2016). All stimuli are available as part of the OSF repository for this article.

727   In addition to the critical minimal pair continua we also recorded three words that did not

728 did not contain any stop consonant sounds ("flare", "share", and "rare"). These word recordings

729 were used as catch trials. Stimulus intensity was set to 70 dB sound pressure level for all

730 recordings.

§4.2.3 Procedure

The code for the experiment is available as part of the OSF repository for this article. A live version is available at (https://www.hlp.rochester.edu//experiments/DLVOT/series-A/experiment-A.html?list_test=NORM-A-forward-test). The first page of the experiment informed participants of their rights and the requirements for the experiment: that they had to be native listeners of English, wear headphones for the entire duration of the experiment, and be in a quiet room without distractions. Participants had to pass a headphone test, and were asked to keep the volume unchanged throughout the experiment. Participants could only advance to the start of the experiment by acknowledging each requirement and consenting to the guidelines of the Research Subjects Review Board of the University of Rochester.

On the next page, participants were informed about the task for the remainder of the experiment. They were informed that they would hear a female talker speak a single word on each trial, and had to select which word they heard. Participants were instructed to listen carefully and answer as quickly and as accurately as possible. They were also alerted to the fact that the recordings were subtly different and therefore may sound repetitive. This was done to encourage their full attention.

Each trial started with a dark-shaded green fixation dot being displayed. At 500ms from trial onset, two minimal pair words appeared on the screen, as shown in Figure **??**. At 1000ms from trial onset, the fixation dot would turn bright green and an audio recording from the matching minimal pair continuum started playing. Participants were required to click on the word they heard. For each participant, /d/-initial words were either always displayed on the left side or always displayed on the right side. Across participants, this ordering was counter-balanced. After participants clicked on the word, the next trial began.

Participants heard 192 target trials (four minimal pair continua, each with 24 VOT steps, each heard twice). In addition, participants heard 12 catch trials. On catch trials, participant saw two written catch stimuli on the screen (e.g., "flare" and "rare"), and heard one of them (e.g. "rare"). Since these recordings were easily distinguishable, they served as a check on participant attention throughout the experiment.

759 The order of trials was randomized for each participant with the only constraint that no

760 stimulus was repeated before each stimulus had been heard at least once. Catch trials were

761 distributed randomly throughout the experiment with the constraint that no more than two catch

762 trials would occur in a row. Participants were given the opportunity to take breaks after every 60

763 trials. Participants took an average of 12 minutes (SD = 4.8) to complete the 204 trials, after

764 which they answered a short survey about the experiment.

765 **§4.2.4   Exclusions**

766 We excluded from analysis participants who committed more than 2 errors out of the 12 catch

767 trials (<83% accuracy, N = 3), participants with an average reaction time (RT) more than three

768 standard deviations from the mean of the by-participant means (N = 0), and participants who

769 reported not to have used headphones (N = 0) or not to be native (L1) speakers of US English (N

770 = 0). For the remaining participants, trials that were more than three SDs from the participant's

771 mean RT were excluded from analysis (1.6%). Finally, we excluded participants (N = 0) who had

772 less than 50% data remaining after these exclusions.

773 **§4.2.5   Analysis approach**

774 The goal of our behavioral analyses was to address three methodological questions that are of

775 relevance to Experiment 2: (1) whether our stimuli resulted in 'reasonable' categorisation

776 functions, (2) whether these functions differed between the four minimal pair items, and (3)

777 whether participants' categorisation functions changed throughout the 192 test trials.

778 To address these questions, we fit a single Bayesian mixed-effects psychometric model to

779 participants' categorization responses on critical trials (e.g., **prins2011?**). The *lapsing model*

780 only contained an intercept (the response bias in log-odds) and by-participant random intercepts.

781 Similarly, the *model for the lapse rate* only had an intercept (the lapse rate) and by-participants

782 random intercepts. No by-item random effects were included for the lapse rate nor lapsing model

783 since these parts of the analysis—by definition—describe stimulus-*in*dependent behavior. The

784 *perceptual model* included an intercept and VOT, as well as the full random effect structure by

785 participants and items (the four minimal pair continua), including random intercepts and random

slopes by participant and minimal pair. We did not model the random effects of trial to reduce model complexity. This potentially makes our analysis of trials in the model anti-conservative. Finally, the models included the covariance between by-participant random effects across the three linear predictors for the lapsing model, lapse rate model, and perceptual model. This allows us to capture whether participants who lapse more often have, for example, different response biases or different sensitivity to VOT (after accounting for lapsing).

We fit the model using the package `brms` (Bürkner, 2017) in R (R Core Team, 2021a; RStudio Team, 2020). Following previous work from our lab (Hörberg & Jaeger, 2021; X. Xie et al., 2021), we used weakly regularizing priors to facilitate model convergence. For fixed effect parameters, we standardized continuous predictors (VOT) by dividing through twice their standard deviation (Gelman, 2008), and used Student priors centered around zero with a scale of 2.5 units (following Gelman et al., 2008) and 3 degrees of freedom. For random effect standard deviations, we used a Cauchy prior with location 0 and scale 2, and for random effect correlations, we used an uninformative LKJ-Correlation prior with its only parameter set to 1, describing a uniform prior over correlation matrices (**Lewandowski2009?**). Four chains with 2000 warm-up samples and 2000 posterior samples each were fit. No divergent transitions after warm-up were observed, and all $\hat{R}$ were close to 1.

§4.2.6 Expectations

Based on previous experiments, we expected a strong positive effect of VOT, with increasing proportions of "t"-responses for increasing VOTs. We did not have clear expectations for the effect of trial other than that responses should become more uniformed (i.e move towards 50-50 "d"/"t"-bias or 0-log-odds) as the experiment progressed (Liu & Jaeger, 2018b) due to the un-informativeness of the stimuli. Previous studies with similar paradigms have typically found lapse rates of 0-10% (< -2.2 log-odds, e.g., Clayards et al., 2008a; Kleinschmidt & Jaeger, 2016).

The lapse rate was estimated to be on the slightly larger side, but within the expected range (7.5 %, 95%-CI: 2.2 to 21.2%; Bayes factor: 1,599 90%-CI : -3.54 to -1.53). Maximum a posteriori (MAP) estimates of by-participant lapse rates ranged from XX . Very high lapse rates were estimated for four of the participants with one in particular whose CI indicated exceptionally high
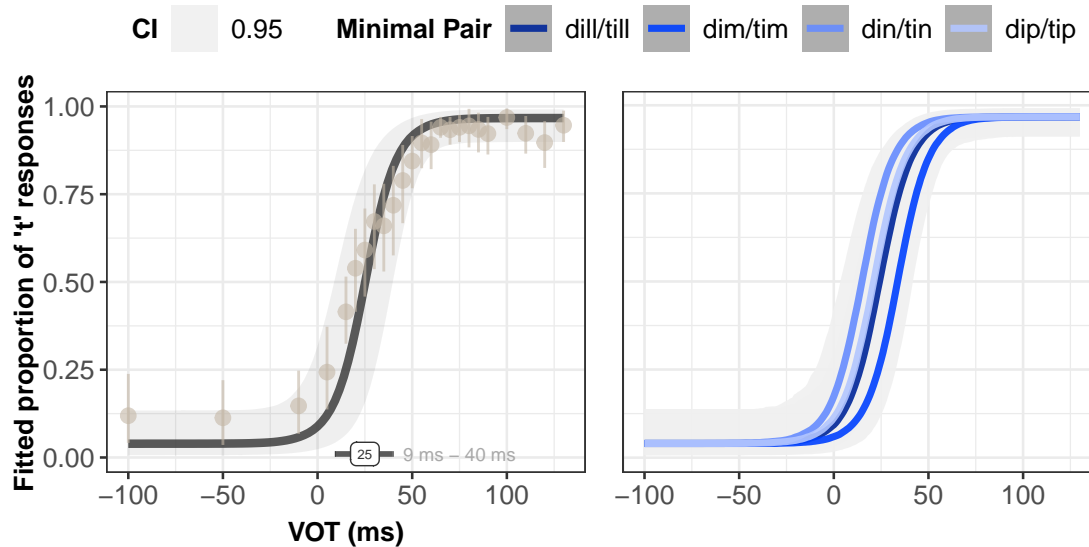
Figure 8. Categorisation functions and points of subjective equality (PSE) derived from the Bayesian mixed-effects psychometric model fit to listeners' responses in Experiment 1. The categorization functions include lapse rates and biases. The PSEs correct for lapse rates and lapse biases (i.e., they are the PSEs of the perceptual component of the psychometric model).[2] **Left:** Effects of VOT, lapse rate, and lapse bias, while marginalizing over trial effects as well as all random effects. Vertical point ranges represent the mean proportion and 95% bootstrapped CIs of participants' "t"-responses at each VOT step. Horizontal point ranges denote the mean and 95% quantile interval of the points of subjective equality (PSE), derived from the 8000 posterior samples of the population parameters. **Right:** The same but showing the fitted categorization functions for each of the four minimal pair continua. Participants' responses are omitted to avoid clutter.

814 uncertainty. These lapse rates might reflect data quality issues with Mechanical Turk that started

815 to emerge over recent years (see **REFS?**; and, specifically for experiments on speech perception,

816 **cummings2023?**), and we return to this issue in Experiment 2.

817   The response bias were estimated to slightly favor "t"-responses (53.4 %, 95%-CI: 17.1 to

818 82.1%; Bayes factor: 1.52 90%-CI : -1.21 to 1.31), as also visible in Figure 8 (left). Unsurprisingly,

819 the psychometric model suggests high uncertainty about the participant-specific response biases,

820 as it is difficult to reliably estimate participant-specific biases while also accounting for trial and

821 VOT effects (range of by-participant MAP estimates: XX). For all but four participants, the 95%

822 CI includes the hypothesis that responses were unbiased. Of the remaining four participants,

823 three were biased towards "t"-responses and one was biased toward "d"-responses.

824   There was no convincing evidence of a main effect of trial ($\hat{\beta}$ = -0.2 95%-CI: -0.6 to 0.4;

Bayes factor: 2.71 90%-CI : -0.57 to 0.26). Given the slight overall bias towards "t"-responses, the

direction of this effect indicates that participants converged towards a 50/50 bias as the test

phase proceeded. This is also evident in Figure 8 (right). In contrast, there was clear evidence for

a positive main effect of VOT on the proportion of "t"-responses ($\hat{\beta} = 12.6$ 95%-CI: 9.8 to 15.5;

Bayes factor: Inf 90%-CI : 10.27 to 15.04). The effect of VOT was consistent across all minimal

pair words as evident from the slopes of the fitted lines by minimal pair 8 (left). MAP estimates

of by minimal pair slopes ranged from . The by minimal-pair intercepts were more varied (MAP

estimates:) with one of the pairs, dim/tim having a slightly lower intercept resulting in fewer

't'-responses on average. In all, this justifies our assumptions that word pair would not have a

substantial effect on categorisation behaviour. From the parameter estimates of the overall fit we

obtained the category boundary from the point of subjective equality (PSE) `r(`

`descale(-(summary(fit_mix)$fixed["mu2_Intercept", 1] /`

`summary(fit_mix)$fixed["mu2_sVOT", 1]), VOT.mean_exp1, VOT.sd_exp1) ms)` which we

use for the design of Experiment 2.

Finally to accomplish the first goal of experiment 1, we look at the interaction between

VOT and trial. There was weak evidence that the effect of VOT decreased across trials ($\hat{\beta}$ = -0.6

95%-CI: -2.6 to 1.4; Bayes factor: 2.76 90%-CI : -2.27 to 1.05). The direction of this

change—towards more shallow VOT slopes as the experiment progressed—makes sense since the

test stimuli were not informative about the talker's pronunciation. Similar changes throughout

prolonged testing have been reported in previous work. (Liu & Jaeger, 2018a, 2019; **REFS?**).

Overall, there was little evidence that participants substantially changed their

categorisation behaviour as the experiment progressed. Still, to err on the cautious side,

Experiment 2 employs shorter test phases.

§4.2.7   Regression analysis - model selection

`## Warning in geom_line(data = fit_mix_f0_data %>% group_by(sVOT) %>% summarise(estimate__ = me`

§4.3   Main experiment
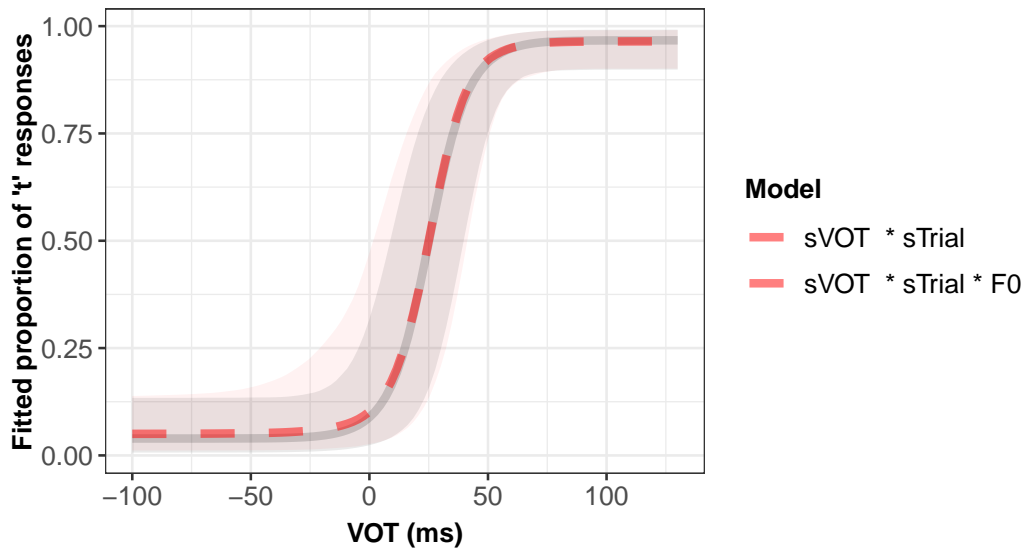
Figure 9. Expected effect of VOT interacting with trial on categorisation from model: 1 + (sVOT + sFO) * sTrial shown as red dashed line with pink shaded CI. Grey line and shaded area represents effects of VOT interacting with trial from model: 1 + sVOT * sTrial

§4.3.1   Catch trial performance plots

-labelled trial performance plots

```
## Warning: Returning more (or less) than 1 row per `summarise()` group was deprecated in dply
## i Please use `reframe()` instead.
## i When switching from `summarise()` to `reframe()`, remember that `reframe()` always return
## Call `lifecycle::last_lifecycle_warnings()` to see where this warning was generated.
```

```
## Warning: Returning more (or less) than 1 row per `summarise()` group was deprecated in dply
## i Please use `reframe()` instead.
## i When switching from `summarise()` to `reframe()`, remember that `reframe()` always return
## Call `lifecycle::last_lifecycle_warnings()` to see where this warning was generated.
```

§4.4   Ideal observer training

We train the IOs on cue distributions extracted from an annotated database of XX L1 US-English talkers' productions (Chodroff and Wilson (2017)) of word initial stops. We apply Bayes' theorem
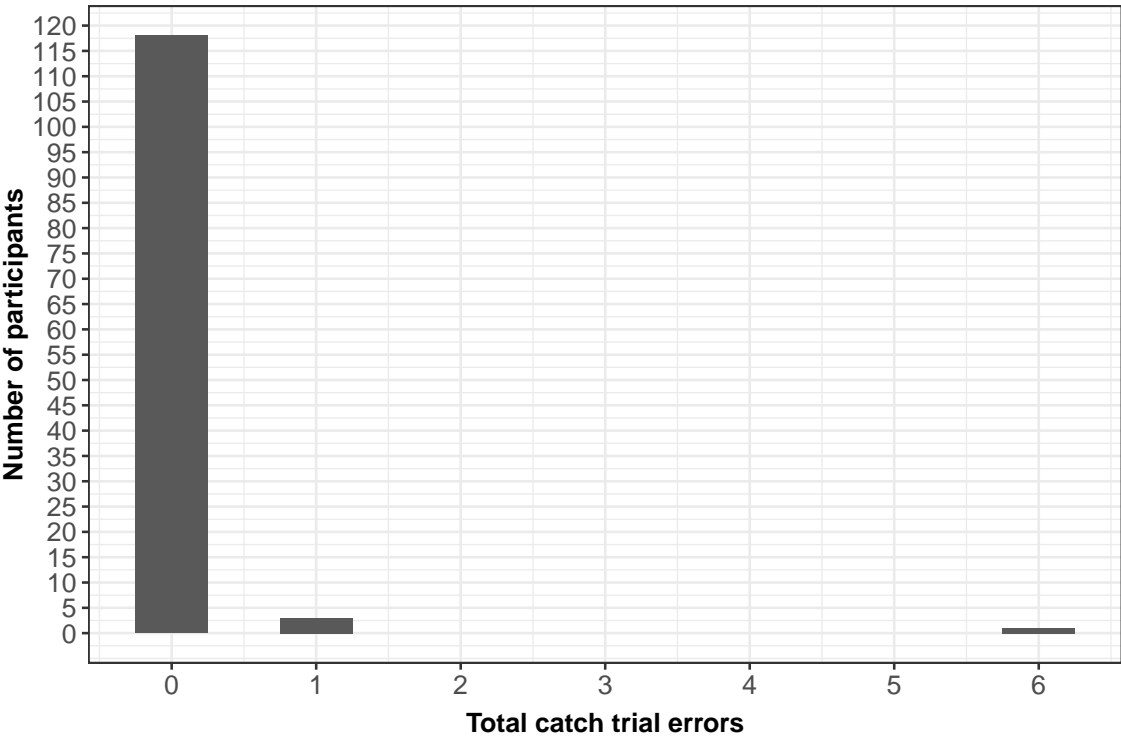
Figure 10. ref:plot-catch-trial-performance
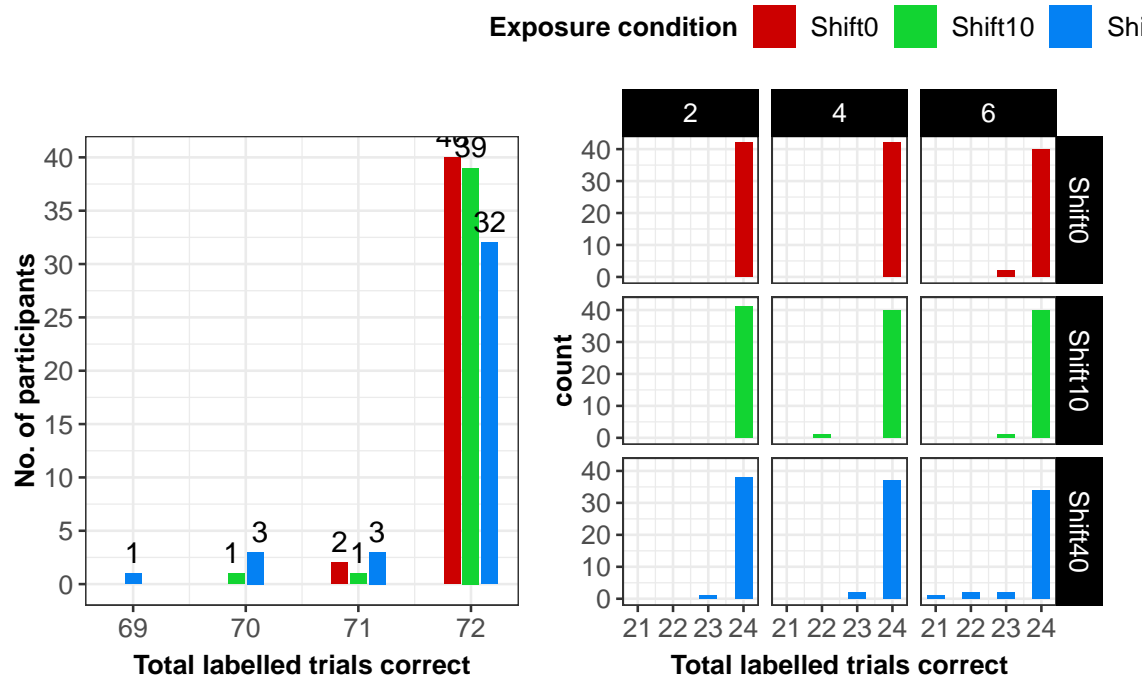
Figure 11
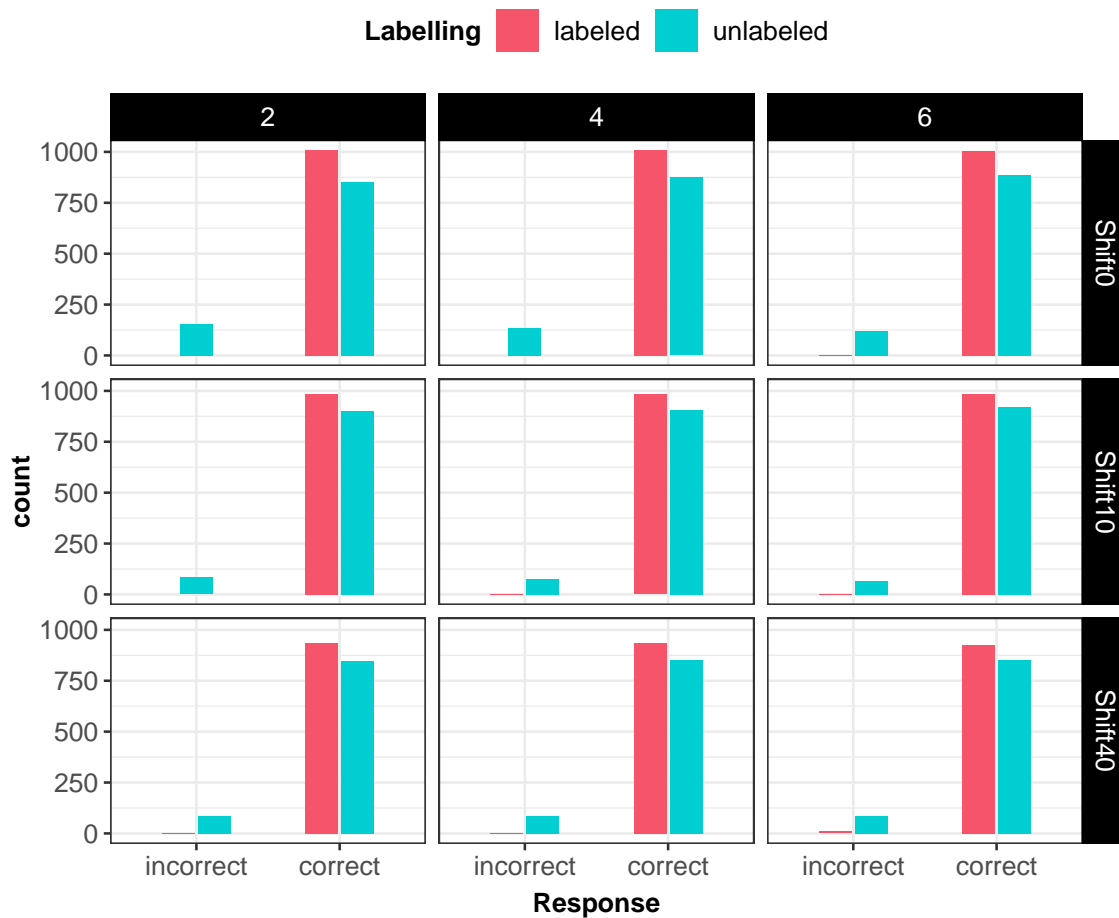
Figure 12

to derive the IOs' posterior probability of categorising the test stimuli as "t". This is defined as

the product of the likelihood of the cue under the hypothesis that the talker produced "t", and

the prior probability of that cue. By using IOs trained solely on production data to predict

categorization behaviour we avoid additional computational degrees of freedom and limit the risk

of overfitting the model to the data thus reducing bias.

We filtered the database to /d/s and /t/s which gave 92 talkers (4x male and 4x female),

each with a minimum of 25 tokens. We then fit ideal observers to each talker under different

hypotheses of distributional learning [and evaluated their respective goodness-of-fit to the human

data]. In total we fit x IOs to represent the different hypotheses about listeners' implicit

knowledge – models grouped by sex, grouped by sex and Predictions of the IO were obtained

using talker-normalized category statistics for /d/ and /t/ from (X. Xie et al., 2022) based on
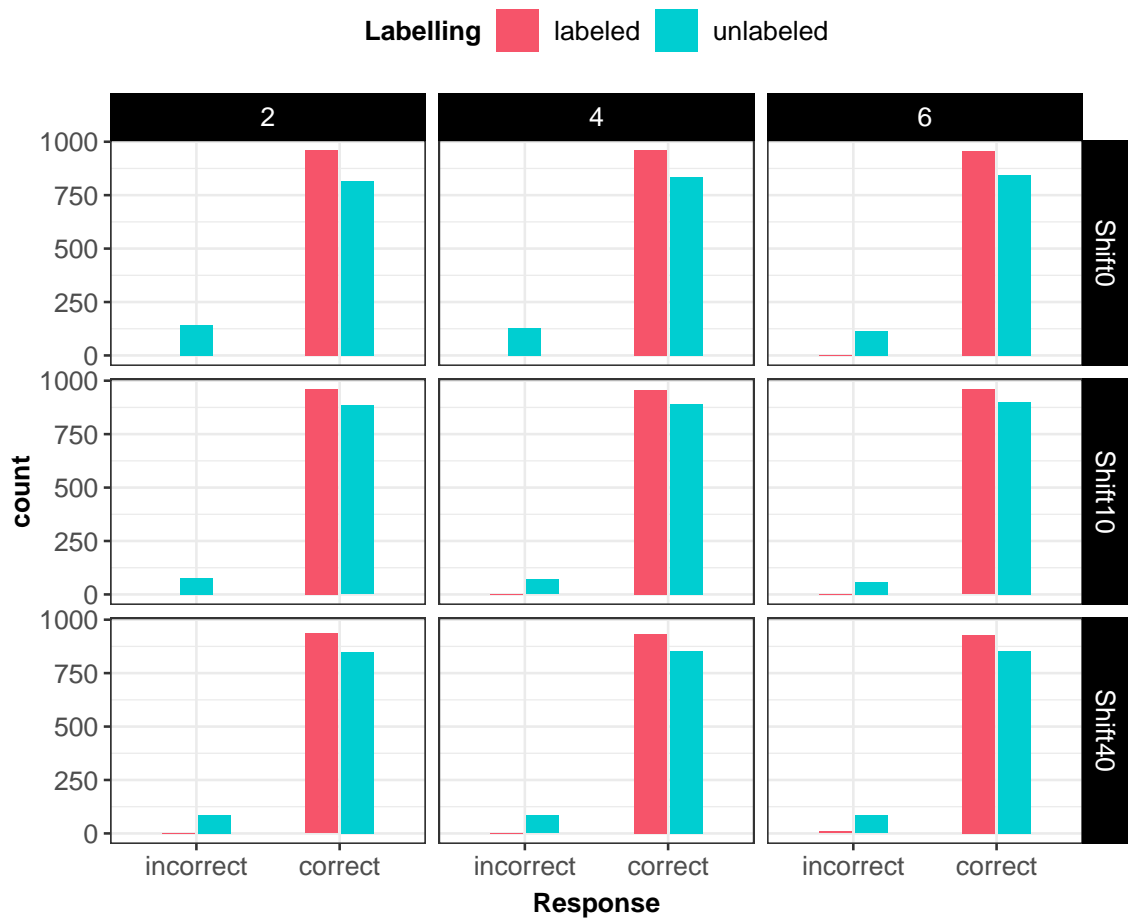
Figure 13

data from (**chodroff2017?**), perceptual noise estimates for VOT from (Kronrod et al., 2016), and
a lapse rate identical to the psychometric model estimate.

§5   Session Info

```
## - Session info ---------------------------------------------------------------------------
##  setting  value
##  version  R version 4.1.3 (2022-03-10)
##  os       macOS Big Sur/Monterey 10.16
##  system   x86_64, darwin17.0
##  ui       X11
```
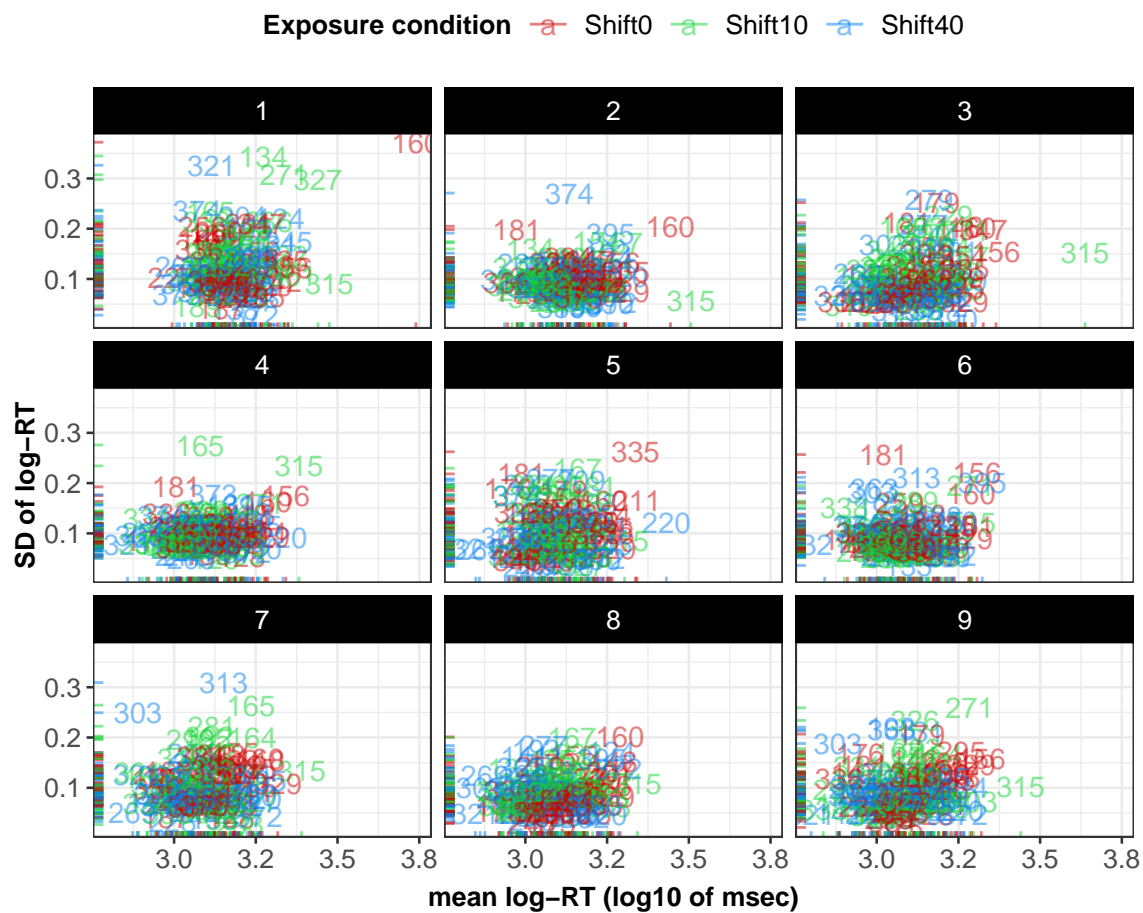
Figure 14
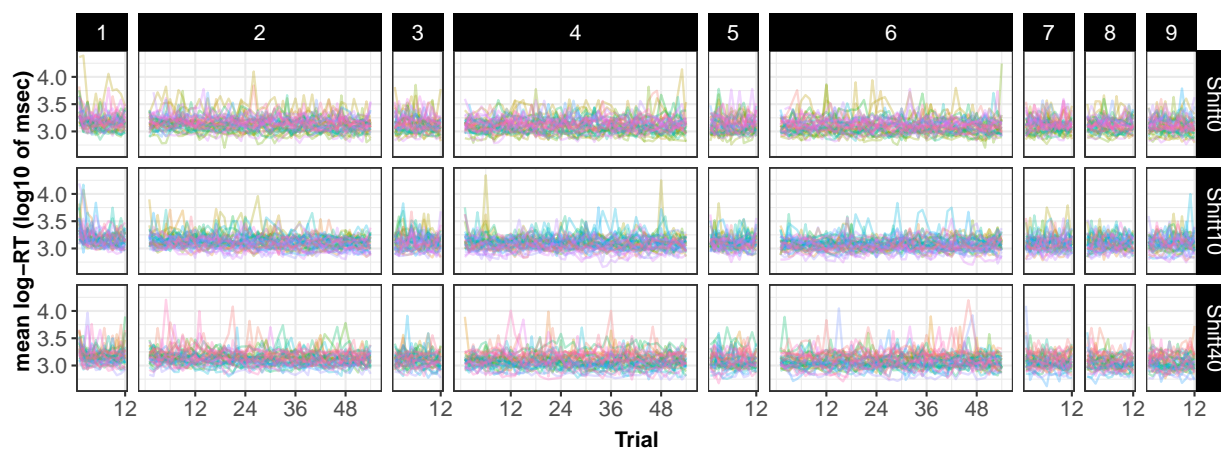
Figure 15
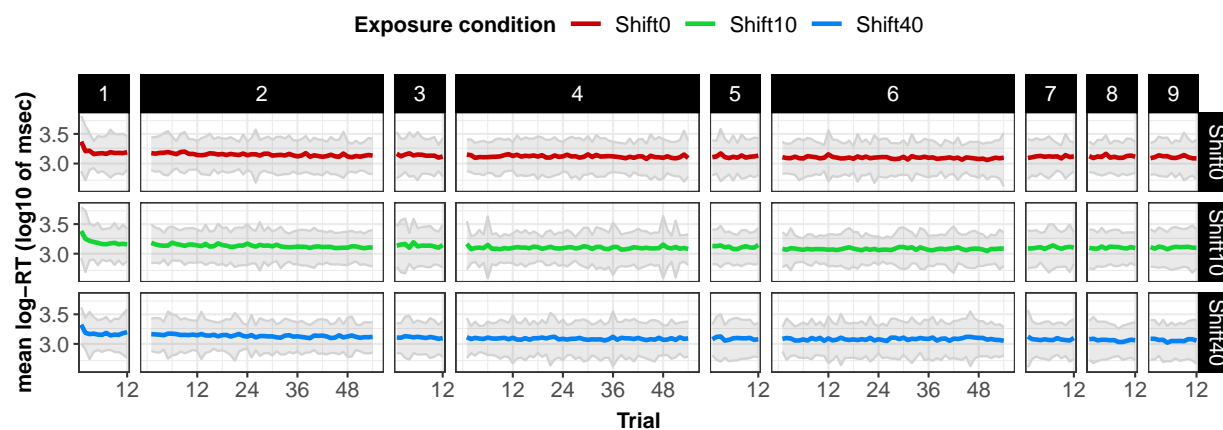
Figure 16

```
884  ##   language (EN)

885  ##   collate   en_US.UTF-8

886  ##   ctype     en_US.UTF-8

887  ##   tz        America/New_York

888  ##   date      2023-05-29

889  ##   pandoc    2.18 @ /Applications/RStudio.app/Contents/MacOS/quarto/bin/tools/ (via rmarkdown)

890  ##

891  ## - Packages -----------------------------------------------------------------

892  ##   package        * version    date (UTC) lib source

893  ##   abind            1.4-5      2016-07-21 [1] CRAN (R 4.1.0)

894  ##   arrayhelpers     1.1-0      2020-02-04 [1] CRAN (R 4.1.0)

895  ##   assertthat     * 0.2.1      2019-03-21 [1] CRAN (R 4.1.0)

896  ##   av               0.8.3      2023-02-05 [1] CRAN (R 4.1.2)

897  ##   backports        1.4.1      2021-12-13 [1] CRAN (R 4.1.0)

898  ##   base64enc        0.1-3      2015-07-28 [1] CRAN (R 4.1.0)

899  ##   bayesplot        1.10.0     2022-11-16 [1] CRAN (R 4.1.2)

900  ##   bayestestR       0.13.1     2023-04-07 [1] CRAN (R 4.1.2)

901  ##   bit              4.0.5      2022-11-15 [1] CRAN (R 4.1.2)

902  ##   bit64            4.0.5      2020-08-30 [1] CRAN (R 4.1.0)

903  ##   bookdown         0.34       2023-05-09 [1] CRAN (R 4.1.3)
```

```
904  ##   boot             1.3-28.1    2022-11-22 [1] CRAN (R 4.1.2)
905  ##   bridgesampling   1.1-2       2021-04-16 [1] CRAN (R 4.1.0)
906  ##   brms           * 2.19.0      2023-03-14 [1] CRAN (R 4.1.2)
907  ##   Brobdingnag      1.2-9       2022-10-19 [1] CRAN (R 4.1.2)
908  ##   broom            1.0.4       2023-03-11 [1] CRAN (R 4.1.2)
909  ##   broom.mixed    * 0.2.9.4     2022-04-17 [1] CRAN (R 4.1.2)
910  ##   cachem           1.0.8       2023-05-01 [1] CRAN (R 4.1.2)
911  ##   callr            3.7.3       2022-11-02 [1] CRAN (R 4.1.2)
912  ##   car              3.1-2       2023-03-30 [1] CRAN (R 4.1.2)
913  ##   carData          3.0-5       2022-01-06 [1] CRAN (R 4.1.2)
914  ##   checkmate        2.2.0       2023-04-27 [1] CRAN (R 4.1.2)
915  ##   class            7.3-22      2023-05-03 [1] CRAN (R 4.1.2)
916  ##   classInt         0.4-9       2023-02-28 [1] CRAN (R 4.1.2)
917  ##   cli              3.6.1       2023-03-23 [1] CRAN (R 4.1.2)
918  ##   cluster          2.1.4       2022-08-22 [1] CRAN (R 4.1.2)
919  ##   coda             0.19-4      2020-09-30 [1] CRAN (R 4.1.0)
920  ##   codetools        0.2-19      2023-02-01 [1] CRAN (R 4.1.2)
921  ##   colorspace       2.1-0       2023-01-23 [1] CRAN (R 4.1.2)
922  ##   colourpicker     1.2.0       2022-10-28 [1] CRAN (R 4.1.2)
923  ##   cowplot        * 1.1.1       2020-12-30 [1] CRAN (R 4.1.0)
924  ##   crayon           1.5.2       2022-09-29 [1] CRAN (R 4.1.2)
925  ##   crosstalk        1.2.0       2021-11-04 [1] CRAN (R 4.1.0)
926  ##   curl           * 5.0.0       2023-01-12 [1] CRAN (R 4.1.2)
927  ##   data.table       1.14.8      2023-02-17 [1] CRAN (R 4.1.2)
928  ##   datawizard       0.7.1       2023-04-03 [1] CRAN (R 4.1.2)
929  ##   DBI              1.1.3       2022-06-18 [1] CRAN (R 4.1.2)
930  ##   devtools         2.4.5       2022-10-11 [1] CRAN (R 4.1.2)
931  ##   digest           0.6.31      2022-12-11 [1] CRAN (R 4.1.2)
932  ##   diptest        * 0.76-0      2021-05-04 [1] CRAN (R 4.1.0)
933  ##   distributional   0.3.2       2023-03-22 [1] CRAN (R 4.1.2)
```

```
934  ##   dplyr         * 1.1.2     2023-04-20 [1] CRAN (R 4.1.2)
935  ##   DT              0.28      2023-05-18 [1] CRAN (R 4.1.3)
936  ##   dygraphs        1.1.1.6   2018-07-11 [1] CRAN (R 4.1.0)
937  ##   e1071           1.7-13    2023-02-01 [1] CRAN (R 4.1.2)
938  ##   effectsize      0.8.3     2023-01-28 [1] CRAN (R 4.1.2)
939  ##   ellipse         0.4.5     2023-04-05 [1] CRAN (R 4.1.2)
940  ##   ellipsis        0.3.2     2021-04-29 [1] CRAN (R 4.1.0)
941  ##   emmeans         1.8.6     2023-05-11 [1] CRAN (R 4.1.2)
942  ##   estimability    1.4.1     2022-08-05 [1] CRAN (R 4.1.2)
943  ##   evaluate        0.21      2023-05-05 [1] CRAN (R 4.1.2)
944  ##   extraDistr      1.9.1     2020-09-07 [1] CRAN (R 4.1.0)
945  ##   fansi           1.0.4     2023-01-22 [1] CRAN (R 4.1.2)
946  ##   farver          2.1.1     2022-07-06 [1] CRAN (R 4.1.2)
947  ##   fastmap         1.1.1     2023-02-24 [1] CRAN (R 4.1.3)
948  ##   forcats       * 1.0.0     2023-01-29 [1] CRAN (R 4.1.2)
949  ##   foreach         1.5.2     2022-02-02 [1] CRAN (R 4.1.2)
950  ##   foreign         0.8-84    2022-12-06 [1] CRAN (R 4.1.2)
951  ##   Formula         1.2-5     2023-02-24 [1] CRAN (R 4.1.3)
952  ##   fs              1.6.2     2023-04-25 [1] CRAN (R 4.1.2)
953  ##   furrr           0.3.1     2022-08-15 [1] CRAN (R 4.1.2)
954  ##   future          1.32.0    2023-03-07 [1] CRAN (R 4.1.2)
955  ##   generics        0.1.3     2022-07-05 [1] CRAN (R 4.1.2)
956  ##   gganimate       1.0.8     2022-09-08 [1] CRAN (R 4.1.2)
957  ##   ggdist          3.3.0     2023-05-13 [1] CRAN (R 4.1.3)
958  ##   ggeffects       1.2.2     2023-05-04 [1] CRAN (R 4.1.2)
959  ##   ggforce         0.4.1     2022-10-04 [1] CRAN (R 4.1.2)
960  ##   ggnewscale    * 0.4.8     2022-10-06 [1] CRAN (R 4.1.2)
961  ##   ggplot2       * 3.4.2     2023-04-03 [1] CRAN (R 4.1.2)
962  ##   ggpubr          0.6.0     2023-02-10 [1] CRAN (R 4.1.2)
963  ##   ggrepel         0.9.3     2023-02-03 [1] CRAN (R 4.1.2)
```

```
964 ## ggridges        0.5.4      2022-09-26 [1] CRAN (R 4.1.2)
965 ## ggsignif        0.6.4      2022-10-13 [1] CRAN (R 4.1.2)
966 ## ggstance      * 0.3.6      2022-11-16 [1] CRAN (R 4.1.2)
967 ## gifski          1.12.0     2023-05-19 [1] CRAN (R 4.1.3)
968 ## globals         0.16.2     2022-11-21 [1] CRAN (R 4.1.2)
969 ## glue            1.6.2      2022-02-24 [1] CRAN (R 4.1.2)
970 ## gridExtra       2.3        2017-09-09 [1] CRAN (R 4.1.0)
971 ## gt            * 0.9.0      2023-03-31 [1] CRAN (R 4.1.2)
972 ## gtable          0.3.3      2023-03-21 [1] CRAN (R 4.1.2)
973 ## gtools          3.9.4      2022-11-27 [1] CRAN (R 4.1.2)
974 ## Hmisc           5.1-0      2023-05-08 [1] CRAN (R 4.1.2)
975 ## hms             1.1.3      2023-03-21 [1] CRAN (R 4.1.2)
976 ## htmlTable       2.4.1      2022-07-07 [1] CRAN (R 4.1.2)
977 ## htmltools       0.5.5      2023-03-23 [1] CRAN (R 4.1.2)
978 ## htmlwidgets     1.6.2      2023-03-17 [1] CRAN (R 4.1.2)
979 ## httpuv          1.6.11     2023-05-11 [1] CRAN (R 4.1.3)
980 ## httr            1.4.6      2023-05-08 [1] CRAN (R 4.1.2)
981 ## igraph          1.3.5      2022-09-22 [1] CRAN (R 4.1.2)
982 ## inline          0.3.19     2021-05-31 [1] CRAN (R 4.1.2)
983 ## insight         0.19.2     2023-05-23 [1] CRAN (R 4.1.3)
984 ## isoband         0.2.7      2022-12-20 [1] CRAN (R 4.1.2)
985 ## iterators       1.0.14     2022-02-05 [1] CRAN (R 4.1.2)
986 ## jsonlite        1.8.4      2022-12-06 [1] CRAN (R 4.1.2)
987 ## kableExtra    * 1.3.4      2021-02-20 [1] CRAN (R 4.1.2)
988 ## KernSmooth      2.23-21    2023-05-03 [1] CRAN (R 4.1.2)
989 ## knitr           1.42       2023-01-25 [1] CRAN (R 4.1.2)
990 ## labeling        0.4.2      2020-10-20 [1] CRAN (R 4.1.0)
991 ## LaplacesDemon   16.1.6     2021-07-09 [1] CRAN (R 4.1.0)
992 ## later           1.3.1      2023-05-02 [1] CRAN (R 4.1.2)
993 ## latexdiffr    * 0.1.0      2021-05-03 [1] CRAN (R 4.1.0)
```

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 994  ##   lattice          0.21-8      2023-04-05 [1] CRAN (R 4.1.2)
 995  ##   lazyeval         0.2.2       2019-03-15 [1] CRAN (R 4.1.0)
 996  ##   lifecycle        1.0.3       2022-10-07 [1] CRAN (R 4.1.2)
 997  ##   linguisticsdown * 1.2.0      2019-03-01 [1] CRAN (R 4.1.0)
 998  ##   listenv          0.9.0       2022-12-16 [1] CRAN (R 4.1.2)
 999  ##   lme4           * 1.1-33      2023-04-25 [1] CRAN (R 4.1.2)
1000  ##   lmerTest         3.1-3       2020-10-23 [1] CRAN (R 4.1.0)
1001  ##   loo              2.6.0       2023-03-31 [1] CRAN (R 4.1.2)
1002  ##   lpSolve          5.6.18      2023-02-01 [1] CRAN (R 4.1.2)
1003  ##   lubridate      * 1.9.2       2023-02-10 [1] CRAN (R 4.1.2)
1004  ##   magick         * 2.7.4       2023-03-09 [1] CRAN (R 4.1.2)
1005  ##   magrittr       * 2.0.3       2022-03-30 [1] CRAN (R 4.1.2)
1006  ##   markdown         1.7         2023-05-16 [1] CRAN (R 4.1.3)
1007  ##   MASS           * 7.3-60      2023-05-04 [1] CRAN (R 4.1.2)
1008  ##   Matrix         * 1.5-1       2022-09-13 [1] CRAN (R 4.1.2)
1009  ##   matrixStats      0.63.0      2022-11-18 [1] CRAN (R 4.1.2)
1010  ##   memoise          2.0.1       2021-11-26 [1] CRAN (R 4.1.0)
1011  ##   mime             0.12        2021-09-28 [1] CRAN (R 4.1.0)
1012  ##   miniUI           0.1.1.1     2018-05-18 [1] CRAN (R 4.1.0)
1013  ##   minqa            1.2.5       2022-10-19 [1] CRAN (R 4.1.2)
1014  ##   modelr           0.1.11      2023-03-22 [1] CRAN (R 4.1.2)
1015  ##   multcomp         1.4-23      2023-03-09 [1] CRAN (R 4.1.2)
1016  ##   munsell          0.5.0       2018-06-12 [1] CRAN (R 4.1.0)
1017  ##   MVBeliefUpdatr * 0.0.1.0002  2023-05-19 [1] Github (hlplab/MVBeliefUpdatr@fae8746)
1018  ##   mvtnorm          1.1-3       2021-10-08 [1] CRAN (R 4.1.0)
1019  ##   nlme             3.1-162     2023-01-31 [1] CRAN (R 4.1.2)
1020  ##   nloptr           2.0.3       2022-05-26 [1] CRAN (R 4.1.2)
1021  ##   nnet             7.3-19      2023-05-03 [1] CRAN (R 4.1.2)
1022  ##   numDeriv         2016.8-1.1  2019-06-06 [1] CRAN (R 4.1.0)
1023  ##   pander           0.6.5       2022-03-18 [1] CRAN (R 4.1.2)
```

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##  papaja       * 0.1.1.9001 2023-05-09 [1] Github (crsh/papaja@1c488f7)
##  parallelly     1.35.0     2023-03-23 [1] CRAN (R 4.1.2)
##  parameters     0.21.0     2023-04-19 [1] CRAN (R 4.1.2)
##  patchwork    * 1.1.2      2022-08-19 [1] CRAN (R 4.1.2)
##  performance    0.10.3     2023-04-07 [1] CRAN (R 4.1.2)
##  phonR        * 1.0-7      2016-08-25 [1] CRAN (R 4.1.0)
##  pillar         1.9.0      2023-03-22 [1] CRAN (R 4.1.2)
##  pkgbuild       1.4.0      2022-11-27 [1] CRAN (R 4.1.2)
##  pkgconfig      2.0.3      2019-09-22 [1] CRAN (R 4.1.0)
##  pkgload        1.3.2      2022-11-16 [1] CRAN (R 4.1.2)
##  plotly         4.10.1     2022-11-07 [1] CRAN (R 4.1.2)
##  plyr           1.8.8      2022-11-11 [1] CRAN (R 4.1.2)
##  png            0.1-8      2022-11-29 [1] CRAN (R 4.1.3)
##  polyclip       1.10-4     2022-10-20 [1] CRAN (R 4.1.2)
##  posterior    * 1.4.1      2023-03-14 [1] CRAN (R 4.1.2)
##  prettyunits    1.1.1      2020-01-24 [1] CRAN (R 4.1.0)
##  processx       3.8.1      2023-04-18 [1] CRAN (R 4.1.2)
##  profvis        0.3.8      2023-05-02 [1] CRAN (R 4.1.2)
##  progress       1.2.2      2019-05-16 [1] CRAN (R 4.1.0)
##  promises       1.2.0.1    2021-02-11 [1] CRAN (R 4.1.0)
##  proxy          0.4-27     2022-06-09 [1] CRAN (R 4.1.2)
##  ps             1.7.5      2023-04-18 [1] CRAN (R 4.1.2)
##  purrr        * 1.0.1      2023-01-10 [1] CRAN (R 4.1.2)
##  R6             2.5.1      2021-08-19 [1] CRAN (R 4.1.0)
##  rbibutils      2.2.13     2023-01-13 [1] CRAN (R 4.1.2)
##  RColorBrewer   1.1-3      2022-04-03 [1] CRAN (R 4.1.2)
##  Rcpp         * 1.0.10     2023-01-22 [1] CRAN (R 4.1.2)
##  RcppParallel   5.1.7      2023-02-27 [1] CRAN (R 4.1.2)
##  Rdpack         2.4        2022-07-20 [1] CRAN (R 4.1.2)
##  readr        * 2.1.4      2023-02-10 [1] CRAN (R 4.1.2)
```

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## remotes        2.4.2    2021-11-30 [1] CRAN (R 4.1.0)
## reshape2       1.4.4    2020-04-09 [1] CRAN (R 4.1.0)
## rlang        * 1.1.1    2023-04-28 [1] CRAN (R 4.1.2)
## rmarkdown      2.21     2023-03-26 [1] CRAN (R 4.1.2)
## rpart          4.1.19   2022-10-21 [1] CRAN (R 4.1.2)
## rsample      * 1.1.1    2022-12-07 [1] CRAN (R 4.1.2)
## rstan          2.21.8   2023-01-17 [1] CRAN (R 4.1.2)
## rstantools     2.3.1    2023-03-30 [1] CRAN (R 4.1.2)
## rstatix        0.7.2    2023-02-01 [1] CRAN (R 4.1.2)
## rstudioapi     0.14     2022-08-22 [1] CRAN (R 4.1.2)
## rvest          1.0.3    2022-08-19 [1] CRAN (R 4.1.2)
## sandwich       3.0-2    2022-06-15 [1] CRAN (R 4.1.2)
## scales         1.2.1    2022-08-20 [1] CRAN (R 4.1.2)
## sessioninfo    1.2.2    2021-12-06 [1] CRAN (R 4.1.0)
## sf             1.0-12   2023-03-19 [1] CRAN (R 4.1.2)
## shiny          1.7.4    2022-12-15 [1] CRAN (R 4.1.2)
## shinyjs        2.1.0    2021-12-23 [1] CRAN (R 4.1.0)
## shinystan      2.6.0    2022-03-03 [1] CRAN (R 4.1.2)
## shinythemes    1.2.0    2021-01-25 [1] CRAN (R 4.1.0)
## sjlabelled     1.2.0    2022-04-10 [1] CRAN (R 4.1.2)
## sjmisc         2.8.9    2021-12-03 [1] CRAN (R 4.1.0)
## sjPlot       * 2.8.14   2023-04-02 [1] CRAN (R 4.1.2)
## sjstats        0.18.2   2022-11-19 [1] CRAN (R 4.1.2)
## StanHeaders    2.26.25  2023-05-17 [1] CRAN (R 4.1.3)
## stringi        1.7.12   2023-01-11 [1] CRAN (R 4.1.2)
## stringr      * 1.5.0    2022-12-02 [1] CRAN (R 4.1.2)
## survival       3.5-5    2023-03-12 [1] CRAN (R 4.1.2)
## svglite        2.1.1    2023-01-10 [1] CRAN (R 4.1.2)
## svUnit         1.0.6    2021-04-19 [1] CRAN (R 4.1.0)
## systemfonts    1.0.4    2022-02-11 [1] CRAN (R 4.1.2)
```

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1084  ##   tensorA          0.36.2   2020-11-19 [1] CRAN (R 4.1.0)
1085  ##   terra          * 1.7-29   2023-04-22 [1] CRAN (R 4.1.2)
1086  ##   TH.data          1.1-2    2023-04-17 [1] CRAN (R 4.1.2)
1087  ##   threejs          0.3.3    2020-01-21 [1] CRAN (R 4.1.0)
1088  ##   tibble         * 3.2.1    2023-03-20 [1] CRAN (R 4.1.3)
1089  ##   tidybayes      * 3.0.4    2023-03-14 [1] CRAN (R 4.1.2)
1090  ##   tidyr          * 1.3.0    2023-01-24 [1] CRAN (R 4.1.2)
1091  ##   tidyselect       1.2.0    2022-10-10 [1] CRAN (R 4.1.2)
1092  ##   tidyverse      * 2.0.0    2023-02-22 [1] CRAN (R 4.1.2)
1093  ##   timechange       0.2.0    2023-01-11 [1] CRAN (R 4.1.2)
1094  ##   tinylabels     * 0.2.3    2022-02-06 [1] CRAN (R 4.1.2)
1095  ##   transformr       0.1.4    2022-08-18 [1] CRAN (R 4.1.2)
1096  ##   tufte            0.12     2022-01-27 [1] CRAN (R 4.1.2)
1097  ##   tweenr           2.0.2    2022-09-06 [1] CRAN (R 4.1.2)
1098  ##   tzdb             0.4.0    2023-05-12 [1] CRAN (R 4.1.3)
1099  ##   units            0.8-2    2023-04-27 [1] CRAN (R 4.1.2)
1100  ##   urlchecker       1.0.1    2021-11-30 [1] CRAN (R 4.1.0)
1101  ##   usethis          2.1.6    2022-05-25 [1] CRAN (R 4.1.2)
1102  ##   utf8             1.2.3    2023-01-31 [1] CRAN (R 4.1.2)
1103  ##   vctrs            0.6.2    2023-04-19 [1] CRAN (R 4.1.2)
1104  ##   viridis          0.6.3    2023-05-03 [1] CRAN (R 4.1.2)
1105  ##   viridisLite      0.4.2    2023-05-02 [1] CRAN (R 4.1.2)
1106  ##   vroom            1.6.3    2023-04-28 [1] CRAN (R 4.1.2)
1107  ##   webshot        * 0.5.4    2022-09-26 [1] CRAN (R 4.1.2)
1108  ##   withr            2.5.0    2022-03-03 [1] CRAN (R 4.1.2)
1109  ##   xfun             0.39     2023-04-20 [1] CRAN (R 4.1.2)
1110  ##   xml2             1.3.4    2023-04-27 [1] CRAN (R 4.1.2)
1111  ##   xtable           1.8-4    2019-04-21 [1] CRAN (R 4.1.0)
1112  ##   xts              0.13.1   2023-04-16 [1] CRAN (R 4.1.2)
1113  ##   yaml             2.3.7    2023-01-23 [1] CRAN (R 4.1.2)
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```
## zoo                1.8-12    2023-04-13 [1] CRAN (R 4.1.2)
##
## [1] /Library/Frameworks/R.framework/Versions/4.1/Resources/library
##
## ----------------------------------------------------------------------------
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