

Structured phonetic variation facilitates talker identification

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Abstract

1 Listeners use talker-specific phonetic structure to facilitate language comprehension. This study
2 tests whether sensitivity to talker-specific phonetic variation also facilitates talker identification.
3 During training, two listener groups learned to associate talkers' voices with cartoon pseudo-
4 faces. For one group, each talker produced characteristically different voice-onset-time values;
5 for the other group, no talker-specific phonetic structure was present. After training, listeners
6 were tested on talker identification for trained and novel words, which was improved for those
7 who heard structured phonetic variation compared to those who did not. These findings suggest
8 an additive benefit of talker-specific phonetic variation for talker identification beyond
9 traditional indexical cues.
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11 **1. Introduction**

12 In order to map the acoustic signal to meaning, listeners must solve the lack of invariance
13 problem for speech, which can arise, for example, because multiple acoustic forms are produced
14 for a given speech sound, or because one or more phonemes of the canonical form may be
15 omitted in a given word. There is a rich literature demonstrating that some variability in speech
16 acoustics is highly structured, including variability associated with talkers' idiolects. For
17 example, talkers show differences in their production of formant frequencies for vowels
18 (Hillenbrand, Getty, Clark, & Wheeler, 1995), spectral center of gravity for fricatives (Newman,
19 Clouse, & Burnham, 2001), and voice-onset-time (VOT) for word-initial stop consonants (Allen,
20 Miller, & DeSteno, 2003; Hullebus, Tobin, & Gafos, 2018 (German); Theodore, Miller, &
21 DeSteno, 2009). In other words, talkers have characteristic idiolectal patterns for acoustic-
22 phonetic properties of speech, including VOT. Listeners can track talkers' characteristic
23 productions (Theodore & Miller, 2010) and dynamically modify the mapping to speech sounds
24 to reflect talker-specific phonetic distributions (e.g., Clayards, Tanenhaus, Aslin, & Jacobs,
25 2008; Theodore, Myers, & Lomibao, 2015). Listeners also show increased word transcription
26 accuracy for familiar compared to unfamiliar talkers (Nygaard & Pisoni, 1998). Collectively,
27 these findings demonstrate that listeners derive talker-specific mappings to speech sounds that
28 serve to facilitate language comprehension.¹

29 The interplay between talker processing and linguistic processing is also observed in the
30 domain of voice processing. Listeners show increased talker identification for talkers speaking a

¹ Unless otherwise indicated in parentheses following each citation, the examined language in cited studies was American English. In English, there is a two-way phonological voicing contrast between short-lag VOTs that cue voiced stops and long-lag VOTs that cue voiceless stops (Lisker & Abramson, 1964).

31 familiar compared to an unfamiliar language [e.g., Goggin, Thompson, Strube, & Simental, 1991
32 (English, German, Spanish)]. There is some evidence to suggest that experience with the
33 linguistic sound structure plays an important role in talker identification, consistent with
34 frameworks that outline *a priori* computational expectations that talker-specific phonetic
35 variation should facilitate voice processing (Kleinschmidt & Jaeger, 2015). For example,
36 listeners who have regular exposure to a nonnative language show increased talker identification
37 for that language compared to listeners without regular exposure (Orena, Theodore, & Polka,
38 2015). Other studies have shown that listeners can identify native-language voices from sine-
39 wave speech analogs (Remez, Fellowes, & Rubin, 1997), a signal manipulation that removes
40 traditional indexical properties (e.g., fundamental frequency) but preserves some idiosyncratic
41 phonetic variation, and that listeners can learn to use VOT as a cue to talker identity for voices
42 that are otherwise identical (Francis & Driscoll, 2006).

43 Neuroimaging findings have shown that brain regions responsible for mapping sound to
44 meaning are sensitive to speaker information in addition to lexical information (Chandrasekaran,
45 Chan, & Wong, 2011). Listeners show sensitivity to voice information at early, pre-attentive
46 stages of processing, challenging the view that cues to voice identity are discarded in the process
47 of mapping speech to meaning (Knösche, Lattner, Maess, Schauer, & Friederici, 2002 (German);
48 Tuninetti, Chládková, Peter, Schiller, & Escudero, 2017 (Dutch, Australian English)). Moreover,
49 brain regions associated with voice processing are also sensitive to talker-specific phonetic
50 variation (Knösche et al., 2002; Myers & Theodore, 2017). In Myers and Theodore (2017),
51 listeners heard two talkers produce characteristically different VOTs for word-initial voiceless
52 stops during a brief exposure phase. Following exposure, neural activation was measured using
53 fMRI while listeners completed a phonetic categorization task for VOTs that were either

54 consistent or inconsistent with their exposure. Of interest to the current work, right
55 temporoparietal regions implicated in voice processing showed sensitivity to the consistency
56 between VOT variant and talker exposure as reflected by increased activation for VOTs that
57 were atypical compared to typical of the speaker based on previous exposure. The observed
58 sensitivity to talker-specific VOT in voice processing neural regions is striking because the
59 talkers' voices differed on a host of traditional indexical properties (e.g., fundamental frequency)
60 in addition to their characteristic difference in VOT production, suggesting that talker-specific
61 phonetic structure can be exploited for voice processing.

62 Here we test this hypothesis directly. In two experiments, two groups of listeners
63 completed a training phase where they heard /g/- and /k/-initial words produced by three female
64 speakers and learned to associate each voice with a cartoon pseudo-face. For one group, there
65 was a structured relationship between VOT and talker, but for the other group, no talker-specific
66 structure was provided. For both groups, the talkers' voices differed with respect to traditional
67 indexical properties and thus sensitivity to phonetic variation was not required to perform the
68 talker identification task (cf. Francis & Driscoll, 2006). After training, both groups completed a
69 talker identification test phase for trained and novel words. The duration of the training phase
70 was very brief (Experiment 1) or relatively longer (Experiment 2). If listeners can in principle
71 use structured phonetic variation to facilitate voice processing over and above the benefit of
72 traditional indexical cues, then we would expect to observe heightened talker identification at
73 test for listeners in the structured compared to the unstructured training group.

74 **2. Experiment 1**

75 *2.1 Participants and stimuli*

76 Forty monolingual speakers of American English (mean = 20 years, SD = 2 years, 28 women, 12

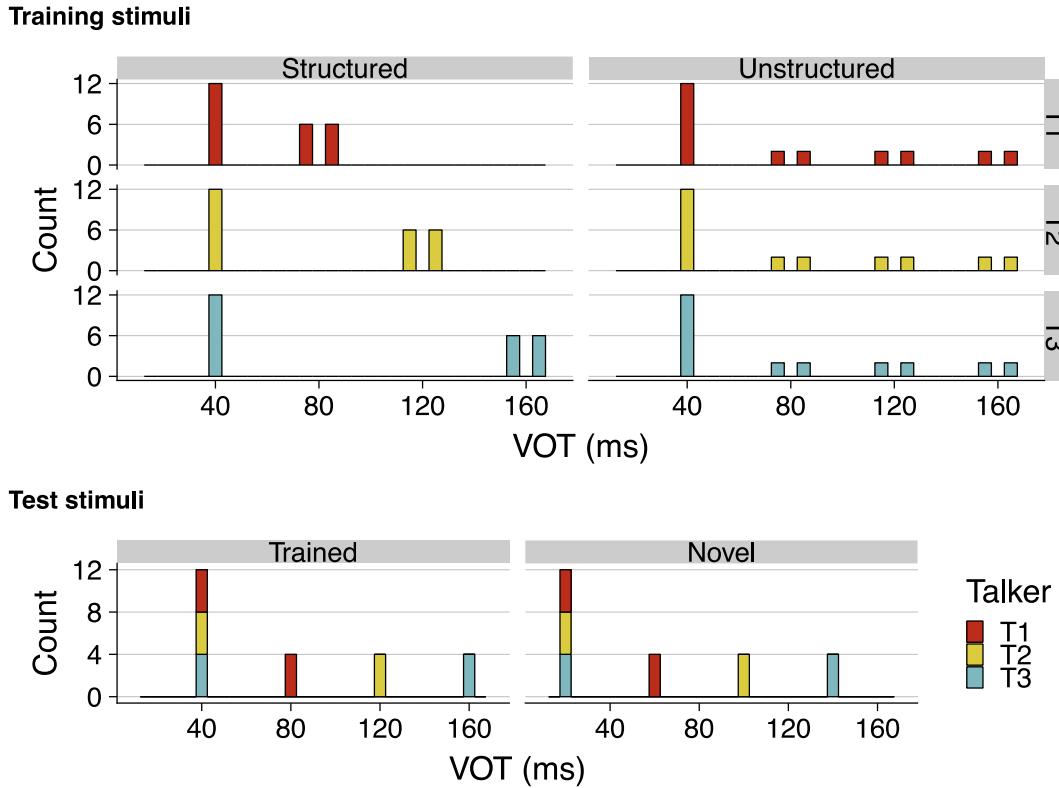
77 men) were recruited from the University of Connecticut community. No participant had a history
78 of speech, language, or hearing disorder per self-report. All participants passed a hearing screen
79 administered at 25 dB for octave frequencies between 500 and 4000 Hz. Listeners received
80 partial course credit or monetary compensation (\$5) for their participation and were randomly
81 assigned to either the structured (n = 20) or unstructured (n = 20) exposure condition.

82 Stimuli consisted of single-word utterances produced by three female speakers of
83 American English with perceptually distinct voices. Stimuli were drawn from four VOT continua
84 (*goal-coal, gain-cane, bowl-pole, bane-pain*) that were created for each talker following methods
85 outlined in Allen and Miller (2004); word duration was equivalent across continua and talkers
86 (ranging between 501 and 511 ms). For each talker and each voiced endpoint (i.e., *goal, gain,*
87 *bowl, bane*), a VOT continuum was created based on the voiced endpoint by successively
88 changing voiced cycles to voiceless cycles using a speech synthesizer (ASL, KayPENTAX,
89 Montvale, NJ), increasing VOT by 4-5 ms with each iteration of the synthesis procedure. This
90 procedure yielded continua that perceptually ranged from voiced to voiceless minimal pairs
91 (e.g., *goal-coal*), with many VOT variants cueing each member of the pair.

92 As shown in Fig. 1, tokens from these continua were selected to form three sets, two for
93 use during training (i.e., structured and unstructured exposure groups) and one for use during
94 test. Both the structured and unstructured training sets contained 72 tokens drawn from the
95 *goal-coal* and *gain-cane* continua that included six repetitions of each voiced-initial word (6
96 repetitions X 2 voiced-initial words X 3 talkers = 36 voiced-initial items) in addition to 36
97 voiceless-initial items. The same voiced-initial items were used in both the structured and
98 unstructured sets, and consisted the voiced endpoints of each continuum; VOTs were equivalent
99 across talker and word (ranging between 35 and 40 ms). For the structured set, the voiceless-

100 initial items consisted of three repetitions of two VOT variants for each word and each talker (3
101 repetitions X 2 VOT variants X 2 words X 3 talkers = 36 voiceless-initial items). The VOT
102 variants were selected so that each talker had a characteristic VOT, with talker 1 producing
103 VOTs of 75 and 85 ms, talker 2 producing VOTs of 115 and 125 ms, and talker 3 producing
104 VOTs of 155 and 165 ms. These ranges span the range of VOTs observed in the literature for
105 American English stops (e.g., Theodore et al., 2009). For the unstructured set, the voiceless-
106 initial items consisted of one repetition of six VOT variants for each talker, corresponding to the
107 VOTs of 75, 85, 115, 125, 155, and 165 ms (1 repetition X 6 VOT variants X 2 words X 3
108 talkers = 36 voiceless-initial items). Accordingly, both the structured and unstructured training
109 sets contained equal numbers of voiced- and voiceless-initial items, and there were equal
110 numbers of each voiceless-initial VOT variant. The critical difference between the two training
111 sets is that a talker-specific structure for voiceless-initial VOTs was present in the structured but
112 not the unstructured training sets.

113 The test set was identical for the two exposure groups and contained the four words used
114 during training (*goal, gain, coal, cane*) and four novel words (*bowl, bane, pole, pain*) for each
115 talker (3 talkers X 2 repetitions X 8 words = 48 test tokens). The voiced-initial tokens (*goal,*
116 *gain, bowl, bane*) were the voiced endpoints of each continuum; as for the *goal* and *gain* tokens,
117 VOTs for the *bowl* and *bane* tokens were equivalent across talker and word (ranging between 15
118 and 20 ms). The voiceless-initial tokens (*coal, cane, pole, pain*) included the VOTs intermediate
119 to those used in the structured exposure set (talker 1 = 80 ms, talker 2 = 120 ms, talker 3 = 160
120 ms) and corresponding VOT tokens from the *bowl-pole* and *bane-pain* continua (talker 1 = 60
121 ms, talker 2 = 100 ms, talker 3 = 140 ms). The shorter VOTs of the labial compared to the velar
122 tokens are consistent with how place of articulation influences VOT (Lisker & Abramson, 1964).



123

124 Fig. 1 (Color online) The top panel shows histograms of VOTs presented during training for the
 125 structured and unstructured exposure conditions. For the structured exposure condition, each
 126 talker (i.e., T1, T2, T3) shows a characteristic VOT production. For the unstructured exposure
 127 condition, there is no characteristic relationship between talker and VOT. The bottom panel
 128 shows histograms of VOTs presented at test for the trained and novel words; the same test
 129 stimuli were used for both exposure groups. For illustration purposes, voiced tokens are plotted
 130 as 40 ms VOT (the trained, velar-initial words) or 20 ms VOT (the novel, labial-initial words); as
 131 described in the main text, the exact VOTs of the voiced-initial words were within 5 ms of these
 132 values.

133 *2.2 Procedure*

134 All testing was completed in a sound-attenuated booth. Auditory stimuli were presented via
 135 headphones at a comfortable listening level held constant across participants. Participants
 136 completed three phases: familiarization, training, and test. Familiarization consisted of 12 trials
 137 (2 repetitions X 2 words X 3 talkers) using the (voiced-initial) *goal* and *gain* tokens that were
 138 selected for the training (and test) phases. On a single trial, the auditory stimulus was presented
 139 along with the cartoon pseudo-face. Participants were told, “Your job is to listen, look, and try to

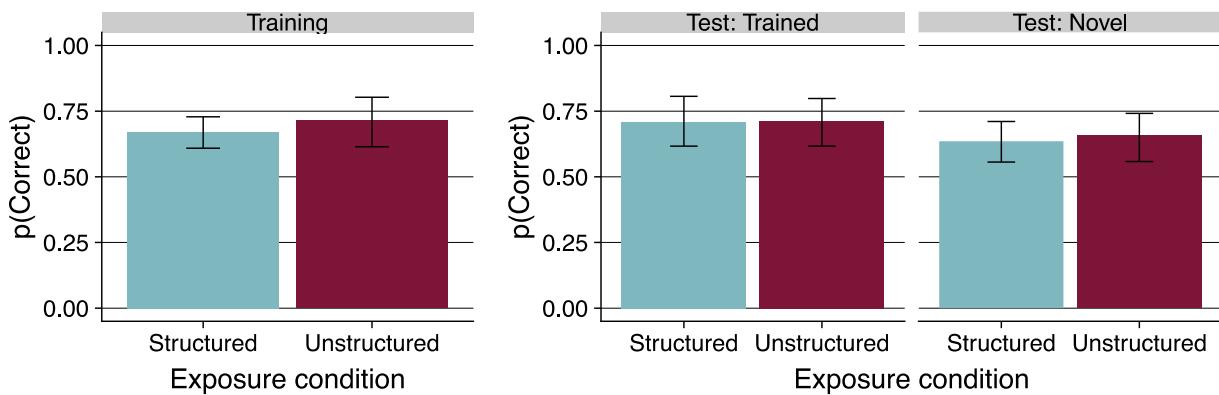
140 remember what that voice sounds like.” No responses were collected during familiarization. The
141 training phase was of fixed length, consisting of one randomization of the 72 items appropriate
142 for the specific exposure group (Fig. 1). On each trial, an auditory stimulus was presented
143 simultaneously with a visual array of three cartoon pseudo-faces. Participants were directed to
144 select the cartoon associated with the talker’s voice by pressing an appropriately labeled button
145 on the response box. Feedback was provided in the form of “Yes!” for correct responses and
146 “No.” for incorrect responses. Trials were separated by an ISI of 2000 ms. The test phase
147 consisted of one randomization of the 48 test stimuli. The procedure was identical to that during
148 training except that no feedback was provided during test. Participants were given a brief break
149 between the training and test phases, and the entire session lasted approximately 15 minutes.

150 *2.3 Results*

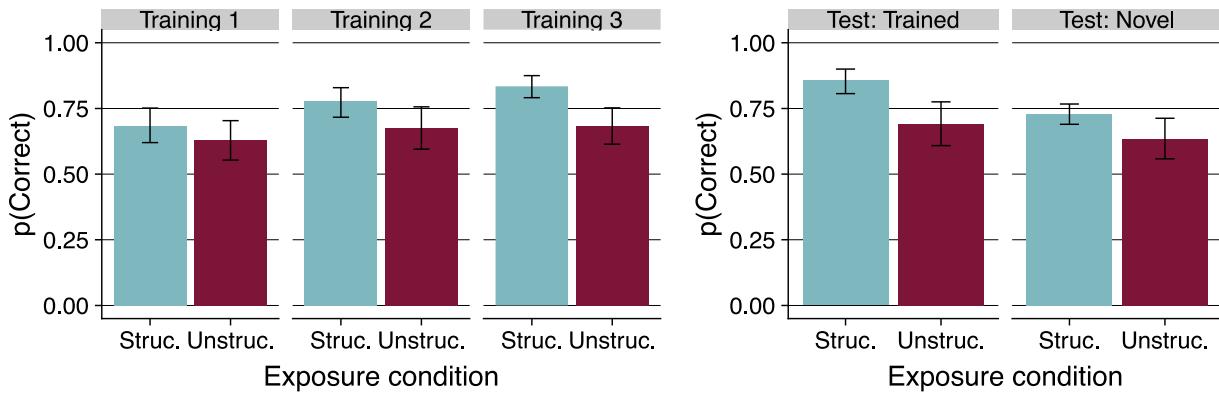
151 The raw data and analysis script for all results presented in this manuscript can be retrieved at
152 https://osf.io/jt37x/?view_only=d682f75915cb4ad4960688d695abcc35. Mean proportion correct
153 talker identification responses for training and test is shown in Fig 2(a). It appears that both
154 groups learned to identify the talkers, given above chance performance at both training and test,
155 and that the magnitude of learning is comparable between conditions. For the training phase,
156 trial-level responses (0 = incorrect, 1 = correct) were analyzed using a generalized linear mixed-
157 effects model (GLMM) with the binomial response family specifying exposure as a fixed effect
158 (structured = 1, unstructured = -1) and random intercepts by subject and talker, implemented
159 using the lme4 package (Bates et al., 2014). The model showed no relationship between
160 exposure condition and talker identification accuracy during training ($\hat{\beta} = -0.154$, $SE = 0.146$, $z =$
161 -1.052 , $p = 0.293$). For the test phase, trial-level responses (0 = incorrect, 1 = correct) were
162 analyzed using a GLMM with the fixed effects of exposure group (structured = 1, unstructured =

163 -1), item type (trained = 1, novel = -1), and their interaction, in addition to random slopes by
 164 subject for item type and random intercepts by subject and talker. Accuracy was higher for
 165 trained compared to novel words ($\hat{\beta} = 0.210$, $SE = 0.066$, $z = 3.186$, $p = 0.001$). There was no
 166 main effect of exposure condition ($\hat{\beta} = -0.023$, $SE = 0.154$, $z = -0.148$, $p = 0.883$), nor an
 167 interaction between item type and exposure condition ($\hat{\beta} = 0.023$, $SE = 0.064$, $z = 0.358$, $p =$
 168 0.720).

Experiment 1



Experiment 2



169

170 Fig. 2 (Color online) The top panel shows mean proportion correct talker identification for the
 171 structured and unstructured exposure groups during training (left) and test (right) for Experiment
 172 1. The bottom panel shows mean proportion correct talker identification during training (left) and
 173 test (right) for the two exposure conditions in Experiment 2. Error bars indicate bootstrapped
 174 95% confidence intervals calculated over by-subject means.

175

3. Experiment 2

177 In experiment 1, listeners successfully learned to identify voices with brief exposure to single-

178 word productions; however, there was no additional benefit given exposure to structured versus
179 unstructured phonetic variation. Experiment 2 tests whether a facilitative effect of structured
180 phonetic variation on talker identification would emerge given a longer exposure period.

181 *3.1 Methods*

182 The participants were 40 monolingual speakers of American English (mean = 20 years,
183 SD = 1 years, 26 women, 14 men) who did not participate in experiment 1 following the criteria
184 outlined previously. Participants were compensated with partial course credit or \$10. Listeners
185 were randomly assigned to either the structured (n = 20) or unstructured (n = 20) exposure
186 condition. The stimuli and procedure for experiment 2 were identical to those used in experiment
187 1 with one critical exception; instead of one block of training (72 trials), listeners completed
188 exactly three blocks of training (216 trials). Each of the three training blocks was a unique
189 randomization of the 72 training items appropriate for each exposure condition, as described for
190 experiment 1. The entire procedure lasted approximately 30 minutes.

191 *3.2 Results*

192 Performance during the training and test phases is shown in Fig. 2. Visual inspection suggests
193 that compared to the unstructured group, the structured group showed (1) greater improvement
194 over the three blocks of training and (2) improved talker recognition at test. Separate GLMMs
195 were constructed for the training and test data, with trial-level accuracy (0 = incorrect, = correct)
196 as the predicted value in each model. The training model contained fixed effects of condition
197 (structured = 1, unstructured = -1) and block (treatment-coded with two contrasts; block 1 as the
198 reference level in each), random slopes by subject for block, and random intercepts by subject
199 and talker. The results showed a main effect of block for both the block 2 vs. block 1 contrast ($\hat{\beta}$
200 = 0.410, $SE = 0.080$, $z = 5.139$, $p < 0.001$) and the block 3 vs. block 1 contrast ($\hat{\beta} = 0.583$, $SE =$

201 0.087, $z = 6.735, p < 0.001$), indicating that talker identification accuracy improved across the
 202 training blocks. There was no main effect of condition ($\hat{\beta} = -0.128, SE = 0.128, z = -1.005, p =$
 203 0.315), nor an interaction between condition and block for the block 2 vs. block 1 contrast ($\hat{\beta} =$
 204 0.143, $SE = 0.078, z = 1.841, p = 0.066$). However, a robust interaction was observed between
 205 condition and block for the block 3 vs. block 1 contrast ($\hat{\beta} = 0.308, SE = 0.085, z = 3.614, p <$
 206 0.001), indicating that those in the structured exposure group improved to a greater degree in
 207 block three compared to block one than those in the unstructured exposure group.

208 The test model contained the fixed effects of exposure condition (structured = 1,
 209 unstructured = -1), item type (trained = 1, novel = -1), and their interaction. Random effects
 210 included random slopes by subject for exposure and item type, and random intercepts by subject
 211 and talker. There was a main effect of exposure ($\hat{\beta} = 0.354, SE = 0.121, z = 2.932, p = 0.003$),
 212 with increased accuracy for the structured compared to the unstructured exposure group, a main
 213 effect of item type ($\hat{\beta} = 0.311, SE = 0.062, z = 5.044, p < 0.001$), with increased accuracy for
 214 trained compared to novel items, and an interaction between exposure and item type ($\hat{\beta} = 0.138,$
 215 $SE = 0.060, z = 2.320, p = 0.020$). Simple effects analyses showed that the item type effect was
 216 reliable for both the structured ($\hat{\beta} = 0.449, SE = 0.091, z = 4.921, p < 0.001$) and unstructured
 217 exposure groups ($\hat{\beta} = 0.173, SE = 0.080, z = 2.128, p = 0.030$), and that the exposure effect was
 218 robust for the trained words ($\hat{\beta} = 0.492, SE = 0.153, z = 3.210, p = 0.001$) but not for the novel
 219 words ($\hat{\beta} = 0.216, SE = 0.113, z = 1.917, p = 0.055$). Thus, the interaction observed in the full
 220 model can be attributed a greater difference between the structured and unstructured exposure
 221 groups for the trained compared to the novel items.

222 **4. Conclusions**

223 Here we examined whether listeners can use structured phonetic variation to facilitate voice

224 processing. Given brief exposure to talkers' voices, access to structured phonetic variation did
225 not show any additional benefit to talker identification beyond the traditional indexical cues (e.g.,
226 fundamental frequency) available to both exposure groups. However, given a more extended
227 period of exposure, listeners who heard talkers produce characteristic VOTs showed improved
228 talker identification compared to listeners who were not exposed to talker-specific phonetic
229 variation. The facilitative effect of talker-specific phonetic variation resulted in an increased rate
230 of learning across the exposure period and increased talker identification accuracy at test
231 primarily for trained words, given the marginal influence of exposure condition on talker
232 identification for novel words. Generalization of talker-specific VOT patterns to a novel place of
233 articulation for talker identification would parallel patterns observed for phonetic processing
234 (Theodore & Miller, 2010) and be consistent with findings showing that talker differences in
235 VOT production are stable across place of articulation (Theodore et al., 2009); however, no
236 robust evidence in support of generalization was observed in the current work.

237 Because the current paradigm provided feedback during training, it may have encouraged
238 explicit learning of the mapping between VOT and talker; as a consequence, the incentive for
239 learning this relationship (for trained items) might be exaggerated compared to more implicit
240 learning paradigms. Though feedback was provided during training, the talkers' voices differed
241 in traditional indexical properties (e.g., fundamental frequency) in addition to the phonetic
242 manipulation, and thus sensitivity to talker-specific phonetic cues was not required in order to
243 learn to identify the talkers' voices. This manipulation is in contrast to Francis and Driscoll
244 (2006), where a difference in within-category VOT was the only cue available to distinguish
245 talkers' voices. Thus, listeners can use talker-specific phonetic variation to facilitate talker
246 identification not only when it is the only cue available (Francis & Driscoll, 2006; Remez et al.,

247 1997), but also when it co-occurs with variation in fundamental frequency and vocal quality. In
248 the current work, the facilitative influence of talker-specific phonetic variation on talker
249 identification was only observed given the longer exposure period provided in experiment 2,
250 suggesting that (1) listeners may require exposure in order to learn talker-specific phonetic
251 structure on a time course that was present in experiment 2 but not in experiment 1, and/or (2)
252 traditional indexical cues to voice identity may be weighted more heavily during initial exposure
253 compared to phonetic cues. One avenue for future research is to examine whether nonnative
254 listeners receive the same benefit for structured phonetic variation as the native listeners tested
255 here; doing so would shed light on potential mechanisms that contribute to the native language
256 benefit for talker identification. Specifically, it may be the case that when perceiving speech in
257 the native language, listeners can use their knowledge of the linguistic sound structure to help
258 parse phonetic variation in the input as a language-general cue versus a talker-specific cue
259 (Kleinschmidt & Jaeger, 2015), but in the absence of expertise with linguistic sound structure,
260 the listener may not be able to determine which aspects of the phonetic stream are licensed by
261 the phonological system versus being attributable to a talker's idiolect (Perrachione & Wong,
262 2007).

263 To conclude, it is well established that there are tight, bi-directional influences between
264 the phonetic processing and indexical processing mechanisms, which are observed behaviorally
265 (Creel & Bregman, 2011; Nygaard & Pisoni, 1998; Theodore & Miller, 2010) and in the neural
266 response to speech input (e.g., Chandrasekaran et al., 2011; Knösche et al., 2002; Myers &
267 Theodore, 2017; Tuninetti et al., 2017). The current results further demonstrate that listeners'
268 sensitivity to talker differences in phonetic properties of speech is one aspect of representational
269 knowledge that mediates the relationship between speech perception and voice processing.

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 275 Acoustical Society of America, Victoria, British Columbia.

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