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Distinct signatures of subjective confidence and objective accuracy in speech prosody

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34 **Abstract**

35

36 Whether speech prosody truly and naturally reflects a speaker's subjective confidence is unclear. Here,
37 using a new approach combining psychophysics with acoustic analysis and automatic classification of verbal
38 reports, we tease apart the contributions of sensory evidence, accuracy, and subjective confidence to speech
39 prosody. We find that the loudness, duration and intonation of verbal reports reflect distinct underlying
40 psychological processes. Strikingly, we show that a speaker's accuracy is encoded in speech prosody beyond
41 their own metacognitive awareness, and that it can be automatically decoded from this information alone with
42 performances up to sixty percent. These findings demonstrate that confidence and accuracy have separable
43 prosodic signatures that are manifested with different timings, and on different acoustic dimensions. Thus,
44 both subjective mental states of confidence, and objective states related to competence, can be directly inferred
45 from natural behaviors such as speech prosody.

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49 **keywords:** subjective confidence; speech prosody; epistemic vigilance; performance monitoring;
50 metacognition; social cognition.

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60 1. Introduction

61

62 Humans' subjective sense of confidence typically reflects an appropriate estimation of the reliability
63 of their own beliefs and decisions (Bang & Fleming, 2018; Barthelmé & Mamassian, 2010), but whether and
64 how this information can truly be perceived by social partners remains unclear. This is an important question
65 because the ability to share subjective states of confidence is crucial for various aspects of human cooperation,
66 ranging from collective decision-making to cultural transmission (Bahrami et al., 2010; Dunstone & Caldwell,
67 2018; Heyes, 2016; Sperber et al., 2010). Past research has documented how speakers deliberately and
68 explicitly communicate their levels of certainty, in particular through language (Aikhenvald, 2018; de Haan,
69 2001; Fusaroli et al., 2012; Sperber et al., 2010). However, morphosyntactic markers of epistemicity greatly
70 vary from one language to the next (Aikhenvald, 2018; de Haan, 2001; Roseano, González, Borràs-Comes, &
71 Prieto, 2016), so such an explicit sharing of subjective confidence requires partners to engage in complex
72 alignment and calibration processes (Bang et al., 2017; Fusaroli et al., 2012) and extensive cultural learning
73 (Goupil & Kouider, 2019; Heyes, Bang, Shea, Frith, & Fleming, 2020).

74 It has been argued that receivers' ability to communicate and monitor senders' confidence and
75 competence is crucial to enable cultures and languages to stabilize in the first place, because mechanisms of
76 epistemic vigilance ensure that misinformation remains limited, and that stable conventional forms can spread
77 (Sperber et al., 2010). If this hypothesis is correct, it is likely that basic mechanisms that do not strictly depend
78 on language and culture should pre-exist to enable humans to detect unreliability from their social partners.
79 This – along with findings showing that communicating states of uncertainty is highly adaptive (Bahrami et
80 al., 2010; Dunstone & Caldwell, 2018; Heyes, 2016) and starts relatively early in life (Goupil, Romand-
81 Monnier, & Kouider, 2016) - suggests that lower-level, more implicit mechanisms allow social partners to
82 quickly and efficiently share their confidence, without the necessary involvement of voluntary control and
83 communicative intentions on the side of senders.

84 Yet, whether and how observers may be able to detect subjective states of confidence directly from
85 their partners' behavior remains unclear. Typically, human adults are able to assess their own performances,
86 which in turn vary with sensory evidence. This means that the three constructs of sensory evidence, objective
87 accuracy and subjective confidence tightly correlate (Bang & Fleming, 2018; Barthelmé & Mamassian, 2010).
88 Thus, whether confidence can truly be perceived from behavior, or only indirectly inferred by observing
89 behavioral manifestations of underlying constructs such as decision-making or perception, is not immediately
90 clear.

91 More fundamentally, there is also considerable debate regarding whether or not confidence reduces to
92 low-level aspects of the decision-making process (Fetsch, Kiani, Newsome, & Shadlen, 2014; Kiani &
93 Shadlen, 2009), or rather, results from distinct higher-order, inferential processes (Fleming & Daw, 2017;
94 Hampton, 2004; Koriat, 2012; Moulin & Souchay, 2015; Proust, 2012). In favor of this second hypothesis,
95 dissociations between objective accuracy and subjective confidence have been observed at the level of the
96 brain (Bang & Fleming, 2018; Cortese, Amano, Koizumi, Kawato, & Lau, 2016). Furthermore, individuals
97 differ in their metacognitive ability to assess their own beliefs and performances (Fleming, Weil, Nagy, Dolan,
98 & Rees, 2010; Navajas et al., 2017), and often show over-confidence biases (Moore & Healy, 2008; Zarnoth
99 & Sniezek, 1997). Beyond inter-individual variability, specific alterations such as unconscious evidence
100 accumulation (Vlassova, Donkin, & Pearson, 2014), stress (Reyes, Silva, Jaramillo, Rehbein, & Sackur, 2015),
101 or targeted pharmacological interventions (Hauser et al., 2017), can lead to dissociations between performances
102 and confidence. It is therefore important to understand whether behavioral manifestations truly reflect
103 subjective confidence, over and beyond lower-level processes tightly linked to decision-making.

104 Yet, candidate natural behaviors that can truly convey subjective confidence, over and beyond
105 objective performances, have so far proved surprisingly difficult to identify. Two studies examined observers'
106 ability to rely on response times to infer others' subjective confidence, and revealed that such inferences
107 crucially depend on an observer's own experience with a task (Koriat & Ackerman, 2010; Patel, Fleming, &
108 Kilner, 2012). This may not be surprising given that the relationships between response times, confidence and

109 accuracy is task-dependent, varying in particular with the speed - accuracy trade off (Pleskac & Busemeyer,
110 2010). More to the point, these results imply that response times are not a good and stable proxy for inferring
111 subjective confidence, and that they can only be exploited to this end when observers have a first-hand
112 experience with observees' task. Similarly, post-decision persistence times have been argued to constitute a
113 directly observable manifestation of confidence in animals (Kepecs, Uchida, Zariwala, & Mainen, 2008) and
114 preverbal infants (Goupil & Kouider, 2016), but other researchers contend that this measure directly reflects
115 the strength or reliability of first-order representations rather than subjective confidence per se (Fleming &
116 Daw, 2017; Insabato, Pannunzi, & Deco, 2016). Thus, so far, a clear behavioral signature of subjective
117 confidence has been lacking, as research focusing on response or persistence times struggled to clearly
118 dissociate genuine behavioral manifestations of subjective confidence from those directly tied to decision-
119 making.

120 Here, we focus on an alternative candidate: speech prosody. It has long been suggested that prosody
121 constitutes one of the fundamental ways through which speakers communicate their levels of confidence
122 (Brennan & Williams, 1995; Scherer, London, & Wolf, 1973; Smith & Clark, 1993). Confident utterances are
123 generally spoken with a falling intonation and louder volumes as compared to doubtful ones (Brennan &
124 Williams, 1995; Jiang & Pell, 2017; Kimble & Seidel, 1991), and listeners are able to decode these prosodic
125 cues to infer a speakers' level of uncertainty (Brennan & Williams, 1995; Goupil, Ponsot, Richardson, Reyes,
126 & Aucouturier, n.d.; Jiang & Pell, 2017), that are seemingly preserved across languages (Chen &
127 Gussenhoven, 2003; Goupil et al., 2020). Yet, the determinants of these prosodic manifestations of confidence
128 in senders (that we hereafter refer to as epistemic prosody) remain unclear, for at least two reasons.

129 First, past research typically relied on methodologies in which actors are asked to deliberately produce
130 utterances with various levels of uncertainty in social contexts. This is known to provide a distorted picture,
131 as requesting participants to produce communicative displays leads them to produce highly stereotypical rather
132 than genuine displays (Juslin, Laukka, & Bänziger, 2018). At a more fundamental level, measuring prosodic
133 displays during social interactions necessarily leads to conflating the contribution of natural, automatic

134 mechanisms, and that of socially induced, deliberate self-presentation mechanisms: speakers do not only show
135 prosodic displays automatically, they can also shape these displays deliberately, for instance in order to
136 persuade (Van Zant & Berger, 2019) or to appear more dominant (Cheng, Tracy, Ho, & Henrich, 2016). Thus,
137 past research leaves open the question of whether epistemic prosody is only displayed when the speaker has a
138 communicative intention, or whether it is constitutively associated with confidence. A first step towards
139 disentangling these influences, and investigating what these prosodic manifestations naturally mean (i.e., a
140 behavior naturally means X when such behavior is typically associated with X; Grice, 1957; Wharton, 2009),
141 can be to measure the relationships between confidence and prosodic features in the absence of an audience,
142 and thus, of self-presentation and socially induced mechanisms. One previous study followed this rationale,
143 and found that confidence impacts speakers' loudness and speech rate even in the absence of an audience
144 (Kimble & Seidel, 1991). This questions the assumption that these prosodic signatures are primarily
145 communicative, and suggests instead that they may reflect confidence constitutively, thereby representing
146 natural signs that the speaker is confident. This study only measured loudness and speech rate however, so it
147 remains unknown whether an important component of epistemic prosody, intonation, is also automatically
148 impacted by confidence in the absence of an audience.

149 Second, typical approaches to this question do not allow discriminating the respective influence of
150 sensory evidence, accuracy and confidence on prosody, because typically the impact of these distinct variables
151 are not measured separately (Brennan & Williams, 1995; Dijkstra, Krahmer, & Swerts, 2006; Jiang, Gossack-
152 Keenan, & Pell, 2020; Jiang & Pell, 2016, 2017; Kimble & Seidel, 1991; Van Zant & Berger, 2019). Thus, it
153 remains unknown what exact psychological variable these prosodic manifestations reflect: do they reflect
154 competence (how accurate speakers actually are), or do they genuinely reveal subjective feelings of confidence
155 (how accurate speakers think they are), thus being akin to non-verbal variants of linguistic expressions such
156 as "I don't know"?

157 A first possibility is that epistemic prosody truly reflects subjective feelings of confidence or doubt.
158 Alternatively, it may be that these prosodic signatures actually reflect lower-level underlying psychological

159 processes such as cognitive effort or fluency, noise in the decision-making process, the availability of the
160 information relevant to the current proposition being uttered (e.g., sensory evidence), or the truth value of the
161 utterance (i.e. the objective accuracy of the speaker). If such was the case, epistemic prosody would reflect
162 competence rather than confidence, and constitute a rather loose proxy to subjective metacognitive states.
163 Finally, a third possibility is that different aspects of prosody (e.g., speech rate, intonation, loudness) reflect
164 different underlying perceptual, cognitive or metacognitive processes. For instance, it may be that – as is the
165 case in neural signals (Fleming & Dolan, 2012) – decision making impacts speech prosody earlier in time,
166 with subjective confidence being reflected only later in the utterance. It may also be that different acoustic
167 dimensions (e.g., loudness, intonation) reflect distinct underlying mental processes.

168 In the present study, we ask whether epistemic prosody reflects a speaker’s metacognition (i.e.,
169 subjective confidence), cognition (i.e., accuracy/competence) or perception (e.g., the amount of sensory
170 evidence that is available to perform a decision), and whether these distinct mental components can be
171 separated from speech prosody alone. We also examine whether speakers’ competence (i.e., their global level
172 of accuracy) and metacognitive sensitivity (i.e., their global ability to monitor their accuracy) modulates how
173 confidence is reflected in their voice, thereby testing the assumptions that explicit metacognition is necessary
174 for individuals to optimally share their confidence (Shea et al., 2014), and that epistemic prosody constitutes
175 an efficient way to filter upcoming social information because it depends on an individual’s level of
176 competence (or meta-competence). Finally, because we are interested in which prosodic signatures naturally
177 reflect a speaker’s level of confidence or competence, over and beyond social influences and self-presentation
178 effects, we test participants in isolation.

179 We address these questions by combining a psychophysical paradigm, signal detection theory, automatic
180 classification analysis, and acoustic analysis of verbal reports produced in a non-social context. Isolated
181 participants’ verbal responses were recorded during a visual detection task allowing to finely manipulate - and
182 measure - sensory evidence, accuracy and confidence (see Figure 1). By analyzing the pitch, intonation,
183 loudness, and duration of these verbal responses as a function of sensory evidence, accuracy and confidence,

184 we find that these psychological processes have distinct prosodic signatures. We then confirm this result by
185 showing that an automatic classifier is able to decode confidence and accuracy orthogonally from speech
186 prosody alone. Finally, we examine individual factors that modulate the automatic expression of prosodic
187 signatures of confidence and competence.

188

189

190 **2. Materials and Methods**

191 ***2.1. Participants.***

192 We tested 40 participants (21 females, mean age 22.8 +/- 3.42 SD) who had no major hearing or visual
193 impairments. This sample size was chosen a priori based on previous studies in our group (Goupil et al., 2020;
194 Ponsot, Burred, Belin, & Aucouturier, 2018), and given constraints associated with other experiments that
195 were run on the same group of participants (see below). Participants signed informed consents before the study,
196 and received a financial compensation. Out of the 40 participants, 32 were students, 4 were employees and 4
197 were unemployed. They were from relatively healthy economic background, with 8 out of 40 participants
198 reporting a household income below the national median; participant's family income was distributed as
199 follows: less than 500 euros (N = 1), between 500 and 2000 euros (7), between 2000 and 5000 (N = 23), above
200 5000 (N=6), not reported (N=3).

201

202 ***2.2. Procedure.***

203 Participants ran three experiments during the same session. In the first and third experiment,
204 participants had to memorize spoken pseudo-words, and to judge whether artificially manipulated voices were
205 more or less reliable respectively. The results from these two experiments address a different set of questions
206 related to speakers' reliability and perception, and will thus be reported in a separate article. The second

207 experiment is the focus of the current paper. In this visual detection task, participants first saw a target bi-
208 syllabic pseudo-word (*bazin, bizan, bivan, bavin, bodou, budou, dejon, dojen, dobue, duboe, vagio, vogia,*
209 *vevon, voven, vizou* or *vuzoi*) that appeared for 16 ms while they were fixating a cross in the middle of the
210 computer screen (see Figure 1). The target could appear at the top or the bottom of the screen, with
211 equiprobable likelihoods. Targets were followed by a surrounding mask after a variable stimulus onset
212 asynchrony (SOA: 16, 50, 83 or 116 ms) in order to induce various level of visibility, and thus, confidence in
213 their verbal response. The mask was presented for 200 ms. Following the mask, the target word (e.g., *bazin*)
214 and an alternative “foil” pseudo-word (e.g., *bazin, bizan*) were presented to the left or right side of the central
215 fixation. Participants were asked to recognize the target word, and to pronounce their verbal response out loud
216 so that it could be recorded. They then reported how well they saw the target on a perceptual awareness (PAS)
217 scale (Ramsøy & Overgaard, 2004), and finally, their confidence in their verbal response on a scale from 1 to
218 4. The experiment was coded in *python* with the *PsychoPy* toolbox (Peirce, 2007). The target word (16
219 possibilities), SOA (4 possibilities), position of the response (2 possibilities: left or right) and position of the
220 target word (2 possibilities: top or bottom) were counterbalanced within participants with a Latin square,
221 resulting in 256 trials per participants. At the end of the session participants were asked to provide information
222 regarding their socio-economic status: they were asked about their level of education, income and occupation,
223 and given the fact that a majority of them were students, we also asked them to provide the same information
224 concerning their parents. These data were aggregated to obtain a composite score of socio-economic status
225 (SES). Participants also filled in a questionnaire assessing their level of empathy, which allows computing a
226 general score over three dimensions measuring cognitive empathy, emotional disconnection and emotional
227 contagion (French version of the BESA, Carré, Stefaniak, D’Ambrosio, Bensalah, & Besche-Richard, 2013).

246 with a simple average of confidence used in previous studies running similar regression analysis, e.g.,
247 Rollwage, Dolan, & Fleming, 2018).

248

249 **2.4. Acoustic analysis.**

250 Recordings were segmented to extract isolated spoken pseudo-words. The fundamental frequency (pitch for
251 short hereafter, in Hz) of each verbal response was then extracted in 20 successive temporal windows using
252 *Praat*, equally dividing the duration of the recording to allow comparisons across trials and participants. Root-
253 Mean-Square (RMS) amplitude was also computed in 20 windows, as well as word durations. Pitch and RMS
254 profiles were then normalized for each participant, word and segment, and duration was normalized for each
255 participant and word (z-scored). To construct the profiles shown in Figure 2, these measures were then
256 averaged separately for each participant, each target word and each level of confidence (high: 3 and 4
257 confidence judgments / low: 1 and 2), and the measures for confident responses were subtracted from the
258 measures for doubtful responses. A similar analysis contrasted correct versus incorrect responses, and short
259 (16 and 50 ms) versus long (83 and 116 ms) SOAs.

260

261 **2.5. Statistics.**

262 Hierarchical linear models were run with pitch, RMS or duration as a dependent variable, and with participant
263 and response word as random factors. Fixed factors included SOA, accuracy and confidence for duration, and
264 SOA, accuracy, confidence and segment for pitch and loudness, in order to account for dynamic aspects.
265 Factors were entered into the model in a hierarchical order from the lowest level (i.e., sensory, SOA) to the
266 highest level (i.e., subjective confidence). We report beta estimates, standard errors, t-values, and p-values
267 estimated through hierarchical model comparisons with the *lme4* and *lmerTest* packages in *R* (Kuznetsova,

268 Brockhoff, & Christensen, 2014). To account for the dynamic effect of confidence on intonation, we relied on
269 the *MNE* package in *python* to identify significant clusters with a permutation test providing p-values corrected
270 for multiple comparisons (Gramfort et al., 2014). The permutation test identified 3 clusters: segments 0 to 1
271 ($p = 0.2$), segments 5 to 11 ($p = 0.012$) and segments 16 to 20 ($p = 0.042$). Pitch was then averaged in the two
272 significant clusters and we examined which variables (SOA, confidence, accuracy) predicted pitch in these
273 two windows separately by running hierarchical linear regressions and mediation analysis with the *mediation*
274 package in *R* (Tingley, Yamamoto, Hirose, Keele, & Imai, 2014).

275 For the regression analysis presented in Figure 5, we ran three (one for each acoustic dimension) linear
276 regressions according to the following formula: Dependent Variable (Euclidean Distance, Loudness or
277 Duration difference score) \sim (Gender + Age + BESA + SES (composite) + Competence + Confidence Bias +
278 Metacognitive Sensitivity) * Measure (Accuracy or Confidence). We report Bonferroni corrected p-values to
279 account for the fact that there were three comparisons (i.e., three acoustic dimensions). Note that similar
280 conclusions were reached with a regression analysis involving as Dependent Variables z-scored Pitch,
281 Duration and RMS values and testing the interaction between all factors and Confidence/Accuracy signaling,
282 although this analysis is less sensible than the one we present here (which relies on Euclidean distance to also
283 consider temporal aspects of intonation).

284

285 **2.6. Machine classification.**

286 We used two types of classification algorithms: k-nearest neighbors (kNN, Figure 4), which were run
287 using a custom-made script, and as a confirmatory method, support-vector machines (SVM, Figure S4) with
288 a radial basis function (RBF) kernel, which were run with the *scikit-learn* toolbox for *python* (Pedregosa et al.,
289 2011). Both types of classifiers have been used extensively in previous research to classify vocalizations in
290 both humans and animals (e.g., see Dezechache, Zuberbühler, Davila-Ross, & Dahl, 2019; Laukka, Neiberg, &

291 Elfenbein, 2014; Piazza, Jordan, & Lew-Williams, 2017...). The classifiers aimed to decode the confidence or
292 the accuracy of the participants from the acoustics properties of their verbal reports, based on distances
293 computed between their pitch, loudness and duration. For each classification method, we conducted two
294 separate classifications for the task of estimating accuracy, and estimating confidence.

295 For the method based on k-nearest neighbors, training and testing datasets for each of the two
296 classifications (i.e., decoding accuracy or confidence) were constructed as follows: a balanced subset of 200
297 speech items was selected pseudo-randomly from the full dataset for each level of the other class: if accuracy
298 was being decoded, a subset was selected for each level of confidence; if confidence was being decoded, a
299 subset was selected for each level of accuracy. The dataset was then randomly divided in 5 folds of 40 items.
300 This set size was chosen so as to allow crossing all combinations of accuracy, SOA and confidence to create
301 balanced datasets (e.g., using training and testing datasets composed of 1/32 of each combinations of accuracy,
302 confidence levels and SOAs). This led to choosing a set size of 100, as the smallest combination of all
303 SOAs/confidence/accuracy was 29. Each fold was thus balanced to contain 50% (i.e., 20 items) of one class
304 level (e.g., correct or high confidence) trials, and 50% of the other class level (e.g., incorrect or low
305 confidence), as well as the same numbers of items for each level of SOA. This equiprobable combinations of
306 conditions ensured that the classifier had to decode the class blindly with respect to the other conditions.
307 Performances were then computed in a 5-fold cross-validation procedure, where one of the folds iteratively
308 served as a “test set”, and the four other folds served as “training test” (Anguita, Ghio, Ridella, & Sterpi, 2009).
309 For each items of the test set, the Euclidean distance between pitch and loudness profiles for this item, and
310 each of the items of the training test, was computed. For duration, a simple difference was computed. For each
311 of the three acoustic dimensions, the 5 smallest distances were then identified, and a prediction of the accuracy
312 or confidence of the test item was made as the most frequent class amongst the nearest neighbors (five for
313 each acoustic dimension). Classifier performance was quantified with the F-value, which is the harmonic mean
314 of the recall and precision of the classifier. In order to allow sufficient resampling of the original dataset, the
315 whole process was repeated and averaged over 20 iterations for each classification. Significance was then

316 assessed with a permutation procedure. For confidence decoding, confidence values were randomly reshuffled
317 for each accuracy level and repetition (i.e., for each fold); for accuracy decoding, accuracy values were
318 randomly reshuffled for each confidence level. Chance-level was then estimated by computing classification
319 performance for these permuted data in the same way as in the real dataset, by computing an F-value. Real
320 and permuted data F-values were then compared by running a rmANOVA with dataset (permuted,
321 randomized) and condition (confidence or accuracy) as independent variables, and repetitions as a repeated
322 measure. Finally, post-hoc differences between permuted and real data were assessed with Tukey post-hoc
323 HSD with false-discovery rate correction for each level of confidence (or accuracy). In order to see if the
324 results would generalize with another classification method, the same analysis was then replicated with SVMs
325 (Figure S4).

326 All data and codes are available on the Open Science Framework (Goupil & Aucouturier, 2020).

327

328

329 **3. Results**

330

331 *3.1. Relationship between sensory evidence, accuracy and confidence.*

332 First, we checked that our experimental paradigm was efficient in inducing various levels of confidence in
333 our participants. A hierarchical linear regression revealed that confidence (four levels) was predicted both by
334 SOA (beta = 0.007 +/- 0.0006 se, t = 10, p < 0.001) and accuracy (beta = 0.85 +/- 0.06 se, t = 13, p < 0.001),
335 and that there was no interaction between these two factors (p > 0.2; see Figure S1.B. and supplementary
336 materials for further details). The fact that confidence increased with SOA over and beyond accuracy is
337 consistent with previous reports suggesting that confidence is also directly impacted by the visibility of the
338 stimulus (Rausch, Hellmann, & Zehetleitner, 2018). We also computed an index of metacognitive sensitivity
339 reflecting the extent to which participants' confidence ratings tracked the reliability of their decisions
340 (Fleming, 2017). Meta-d' was better than chance for every SOA (all p-values < 0.001, see Figure S1.D), and

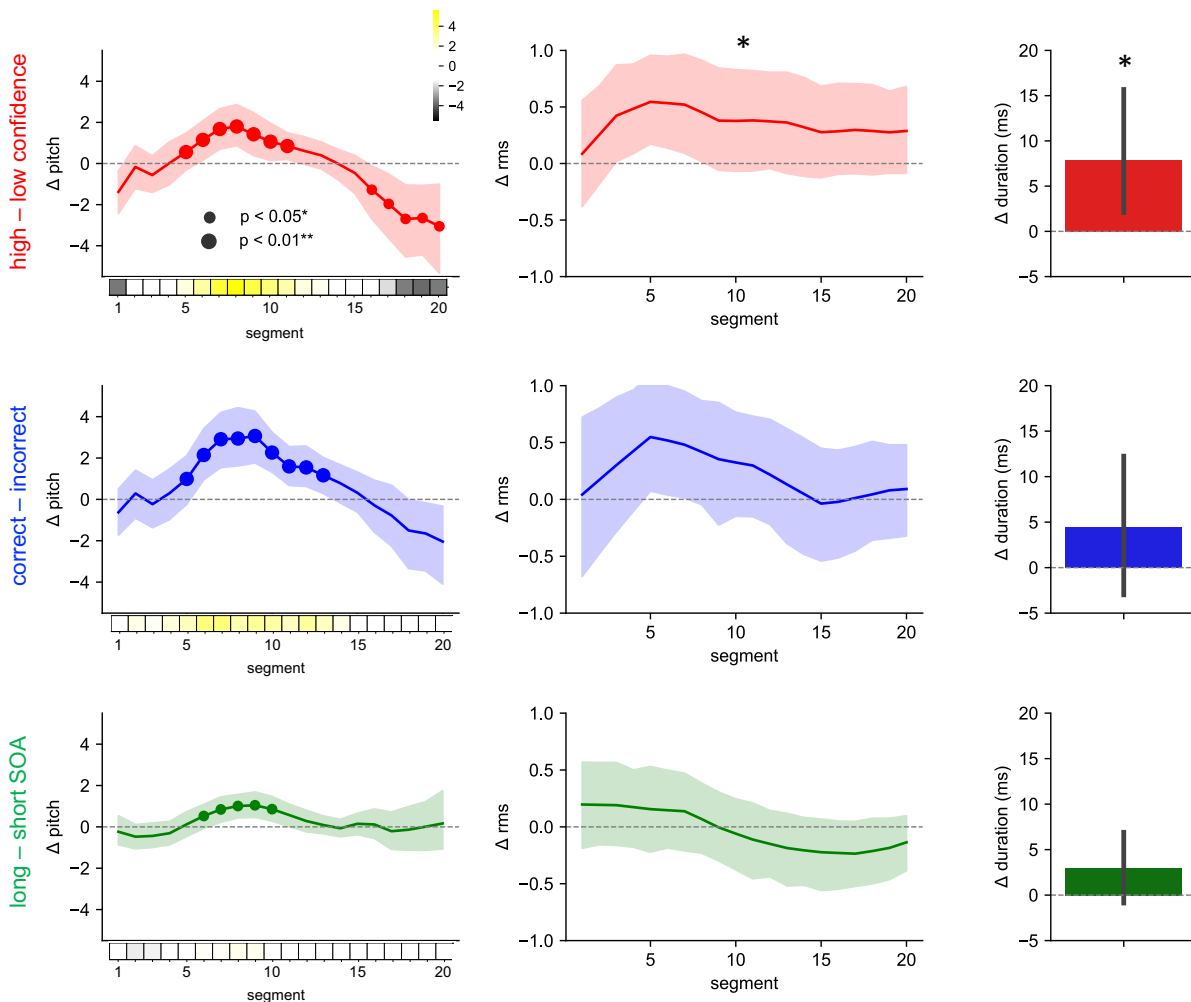
341 increased with SOA ($F(1,39) = 74, p < 0.001, \eta p^2 = 0.65$), a finding that is consistent with previous research
342 relying on similar visual paradigms (Charles, Van Opstal, Marti, & Dehaene, 2013; Kunitomo, Miller, &
343 Pashler, 2001). Meta-d' was significantly above chance for seen stimuli (glimpse: $M = 1.36 \pm 0.88, t(39) =$
344 $6.2, p < 0.001, \text{Cohen's } d = 1.4$; almost clear: $M = 1.19 \pm 0.72, t(39) = 5.97, p < 0.001, \text{Cohen's } d = 1.35,$
345 clear: $M = 2.55 \pm 1.27, t(39) = 10.12, p < 0.001, \text{Cohen's } d = 2.29$), but it was not significantly better than
346 chance for unseen stimuli ($M = 0.59 \pm 1.24, t(39) = 0.46, p = 0.64, \text{Cohen's } d = 0.1$). This result is in line
347 with research suggesting that metacognitive sensitivity depends on conscious access (Persaud, McLeod, &
348 Cowey, 2007), but contrasts with other studies reporting that metacognitive sensitivity can be better than
349 chance even for unseen stimuli (Charles et al., 2013). This may be due to the fact that we rely on verbal reports
350 here, and this hypothesis could be specifically explored in further studies.

351

352 ***3.2. Speech prosody reflects subjective confidence, even in the absence of an audience.***

353 We then turned to the analysis of vocal productions. First, we wanted to compare the prosody of doubtful
354 and confident responses, to confirm that prosodic markers of confidence are present in speech even in a non-
355 social context, as expected from a previous study that only examined global loudness and speech rate (Kimble
356 & Seidel, 1991). To this end, we extracted the duration, pitch profiles and loudness profiles of each verbal
357 response. As can be seen in Figure 2 and Figure S2, compared to doubtful responses, confident responses were
358 characterized by rising - falling intonation (LHL%), longer duration, and increased volume - mostly
359 concentrated at the beginning of the word.

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Figure 2. Acoustic analysis of verbal responses. Pitch, loudness (RMS) and duration values for high minus low confidence trials (1-2 versus 3-4; top – red), correct minus incorrect trials (middle – blue) and long (85-116) minus short (16-50ms) SOAs (bottom–green). Pitch: for the contrast between high and low confidence, the permutation test revealed two significant clusters: the first one ranging from the 5th to the 11th segment ($p = 0.008$), and the second ranging from the 16th to the 20th segment $p = 0.036$). For the contrast between correct and incorrect responses, the permutation test revealed one significant cluster ($p = 0.002$) from the 5th to the 13th segment. For the contrast between high and low SOAs, the permutation test revealed one significant cluster ($p = 0.017$) from the 6th to the 10th segment. RMS: the permutation test revealed no significant clusters with the threshold of $p < 0.05$. Circles represent the significant clusters obtained with the permutation test (small circles significance threshold of $p < 0.05$, bigger circles: $p < 0.01$). Shaded areas and error bars show 95% confidence intervals. * represents the significant difference between the average acoustic features of high versus low confidence responses (paired t-test, threshold of $p < 0.05$). Heatmaps show the t-values of the hierarchical regression computed separately in each of the twenty temporal windows and including all three (SOA, accuracy and confidence) factors.

375 Regarding mean pitch, there was no significant differences between confident and doubtful responses
376 (mean difference in pitch = -0.23 ± 2.16 , $t(39) = -0.7$, $p = 0.5$, Cohen's $d = 0.1$). This contrasts with previous
377 research involving actor-produced speech (Jiang & Pell, 2017), or speakers whose intention is to persuade
378 their interlocutors (Van Zant & Berger, 2019), that have produced discrepant findings concerning the relation
379 between mean pitch and confidence. Our result suggests that such discrepancy may be due to focusing on
380 mean pitch, that is likely to be associated to social traits (e.g., dominance, trustworthiness), rather than to

381 attitudes such as confidence, that are more related to dynamic aspects of pitch (i.e., intonation, Goupil et al.,
382 n.d.; McAleer, Todorov, Belin, Taylor, & Iredell, 2014; Ponsot et al., 2018). Mean pitch may also be easier to
383 manipulate than intonation for speakers asked to persuade or simulate confidence, which would provide a
384 distorted picture of what “confident” prosodies naturally sound like due to social influences and self-
385 presentation effects.

386 By contrast, as expected intonation (i.e., evolutions of the pitch over time) was impacted by confidence: a
387 rmANOVA revealed an interaction between the level of confidence (including the full range of responses from
388 1 to 4) and segment ($F(1,39) = 7.3$, $p = 0.013$, $\eta^2 = 0.01$), as well as main effects of both segment ($F(1,39) =$
389 4.1 , $p < 0.05$, $\eta^2 = 0.08$) and confidence level ($F(1,39) = 5.5$, $p < 0.03$, $\eta^2 = 0.01$). As can be seen in Figure
390 2 and S2 this interaction reflects the fact that confident responses present a rise and fall pattern, while doubtful
391 responses present the opposite fall and rise pattern.

392 Regarding loudness, there was a static effect such that confident responses were louder than doubtful ones
393 (mean difference = 0.36 ± 1 , $t(39) = 2.15$, $p = 0.038$, $d = 0.34$). A rmANOVA also revealed a main effect of
394 segment ($F(1,39) = 183$, $p < 0.001$, $\eta^2 = 0.78$) and confidence level ($F(1,39) = 5.25$, $p < 0.03$, $\eta^2 = 0.02$)
395 but no interaction ($F < 1$), suggesting that contrary to pitch, the effect was global rather than dynamic.

396 Overall, the pattern of intonation and loudness observed in participants’ verbal productions was consistent
397 with previous results obtained in social contexts (Brennan & Williams, 1995; Dijkstra et al., 2006; Jiang &
398 Pell, 2017). These results confirm that these two acoustic parameters are consistent indices that can be used
399 by listeners to infer the confidence of a speaker, and show that these prosodic manifestations of confidence
400 are constitutively present even in the absence of an audience. The fact that loudness and duration still reflect
401 confidence in the absence of an audience was known (Kimble & Seidel, 1991), but our results extend this
402 finding to intonation.

403 Regarding duration, we found that confident responses were longer than doubtful responses (mean
404 difference = 7.85 ± 21.4 , $t(39) = 2.3$, $p = 0.027$, $d = 0.37$). This is inconsistent with previous reports that
405 confident responses are produced with a faster speech rate (Jiang & Pell, 2017; Scherer et al., 1973), and also

406 with some results obtained in perception (Goupil et al., n.d.). Thus, like response times, speech rate may not
 407 be a stable index enabling listeners to infer the reliability of a speaker. This is potentially due to the fact that
 408 the relationship between response speed, accuracy and confidence greatly varies depending on task
 409 characteristics such as the speed accuracy trade off (our task here was speeded, which would typically lead to
 410 slower response speed for correct and confidence responses) (Pleskac & Busemeyer, 2010). Interestingly,
 411 previous research has also shown that experience with the contingencies of a task is required to make accurate
 412 inferences about how response times relate to confidence in others (Koriat & Ackerman, 2010; Patel et al.,
 413 2012). In order to further elucidate the precise relationship between speech rate and confidence, further
 414 research relying on the method that we develop here could systematically vary the speed accuracy trade-off.

415 Regardless of these fine-grained aspects, the presence of prosodic markers of confidence in the absence of
 416 an interlocutor confirms that they constitute natural signs (Kimble & Seidel, 1991), that are present even when
 417 speakers have no deliberate intention to communicate their uncertainty. Next, we wanted to determine what
 418 these prosodic markers really reflect: metacognition, cognition, or perception?

419

420 ***3.3. Respective contributions of sensory evidence, accuracy and confidence to speech prosody.***

421 To this aim, we also computed differential prosodic profiles for correct versus incorrect responses, and
 422 long versus short SOAs. As can be seen in Figure 2, we observed that both accuracy (middle row) and SOA
 423 (bottom row) were also reflected to some extent in prosody. To elucidate whether prosody is specifically linked
 424 to confidence or related to other underlying variables, we ran hierarchical linear mixed regressions assessing
 425 the impact of SOA (four durations), accuracy (two levels) and confidence (four levels) on duration, loudness
 426 and pitch (see Table 1 for the full outputs of the models).

427

428

429

time window	dependent variable	independent variable	beta	se	t	p
global	duration	SOA	0.0001	0.0003	0.37	0.71
		accuracy	0.007	0.03	-0.22	0.82
		confidence	0.035	0.01	3	0.003

		SOA:confidence	0.0004	0.0003	1.21	0.22
		accuracy:confidence	0.03	0.027	1.31	0.19
		SOA:accuracy	0.0008	0.0009	0.9	0.37
	loudness	SOA	-0.0002	-0.0002	-0.92	0.36
		accuracy	0.07	0.03	2.7	0.007
		confidence	0.013	0.01	1.24	0.21
		SOA:confidence	0.00001	0.0002	0.05	0.96
		accuracy:confidence	0.0007	0.002	0.03	0.98
		SOA:accuracy	-0.0006	-0.0008	-0.81	0.42
		SOA	-0.0004	0.0002	-1.9	0.052
	pitch	accuracy	0.017	0.016	1.07	0.29
		confidence	0.08	0.008	10.7	< 0.001
		SOA:confidence	-0.0002	-0.00006	-3.1	0.002
		accuracy:confidence	-0.054	0.006	-8.8	< 0.001
		SOA:accuracy	0.0004	0.0002	1.94	0.053
		SOA:segment	0.00001	0.000009	1.34	0.18
		accuracy:segment	-0.001	0.0008	-1.63	0.1
confidence:segment	-0.002	0.0004	-5.53	< 0.001		
first cluster (segments 5 to 11)	pitch	SOA	0.0003	0.0002	1.27	0.2
		accuracy	0.06	0.025	2.4	0.016
		confidence	0.08	0.02	4.2	< 0.001
		SOA:confidence	-0.0002	0.0002	-0.9	0.37
		accuracy:confidence	-0.05	0.02	-2.4	0.015
		SOA:accuracy	-0.0002	0.0006	-0.3	0.77
second cluster (segments 16 to 20)	pitch	SOA	-0.00006	0.0003	-0.26	0.79
		accuracy	0.005	0.03	0.18	0.86
		confidence	-0.03	0.01	-3	0.002
		SOA:confidence	0.00006	0.0002	0.23	0.81
		accuracy:confidence	-0.04	0.02	-1.94	0.052
		SOA:accuracy	0.001	0.0008	2.02	0.044

Table 1. Results of the linear mixed regressions testing the impact of SOA, accuracy and confidence on the duration, loudness and pitch of participants' verbal responses, computed in the whole 20 segments window (top) or in the two significant clusters windows (bottom; this analysis was conducted only for pitch as interactions with segments were not significant for loudness). We also report the interactions between SOA / accuracy / confidence and segments (e.g., SOA:segment), and interactions between variables (e.g., SOA:confidence). Shaded cells show significant results with the lightest shade corresponding to $p < 0.05$ and the darkest shade to $p < 0.001$.

For duration, we included SOA, accuracy and confidence as fixed factors, plus interactions between these factors, and participant and target word as random factors. The regression revealed that duration was significantly predicted by confidence (beta = 0.035 +/- 0.01 se, $t = 3$, $p = 0.003$), but not significantly so by accuracy ($p > 0.7$) and SOA ($p > 0.8$) when the three covariates were present in the model. In addition, there were no significant interactions between the three acoustic dimensions (all p -values > 0.1). Thus, overall, duration was predicted by subjective confidence rather than underlying variables, with confident responses being spoken slower than doubtful responses.

For pitch and loudness, we ran a similar model that also included interactions with segment, since these two acoustic parameters typically vary across time. Regarding loudness, there were no interactions with

446 segment (all p-values > 0.8) however, revealing that the effects were mostly non-dynamic for this acoustic
447 dimension; we therefore reduced the model to the static model used for duration above. This static model
448 revealed a main effect of accuracy (beta = 0.07 +/- 0.03 se, t = 2.7, p = 0.007), while the main effect of
449 confidence (p = 0.21) and SOA (p = 0.36) were not significant when entering the three co-variates into the
450 model. Furthermore, there were no interactions between the three variables (all p-values > 0.2). Hence, it
451 appears that loudness primarily reflects accuracy rather than confidence per se, or sensory evidence.

452 Regarding pitch, we found a significant main effect of confidence (beta = 0.08 +/- 0.008 se, t = 10.7, p
453 < 0.001), but the effects of accuracy (beta = 0.017 +/- 0.016 se, t = 1.07, p = 0.29) and SOA (beta = -0.0004
454 +/- 0.0002 se, t = -1.9, p = 0.052) were not significant when entering the three co-variates into the model.
455 Importantly, there was also a significant interaction between segment and confidence (beta = -0.002 +/- 0.0004
456 se, t = -5.53, p < 0.001), reflecting the fact that this effect was dynamic (the interaction with segment did not
457 reach significance for accuracy: p = 0.1, nor SOA: p = 0.18). While in low confidence trials participant's
458 intonation presented a typical fall and rise pattern (HLH%), in high confidence trials it presented the opposite
459 rise and fall (LHL%) pattern (see Figures 1B and S2). Finally, there was also an interaction between confidence
460 and accuracy (beta = -0.054 +/- 0.006 se, t = -8.8, p < 0.001) and confidence and SOA (beta = -0.0002 +/-
461 0.00006 se, t = -3.1, p < 0.01).

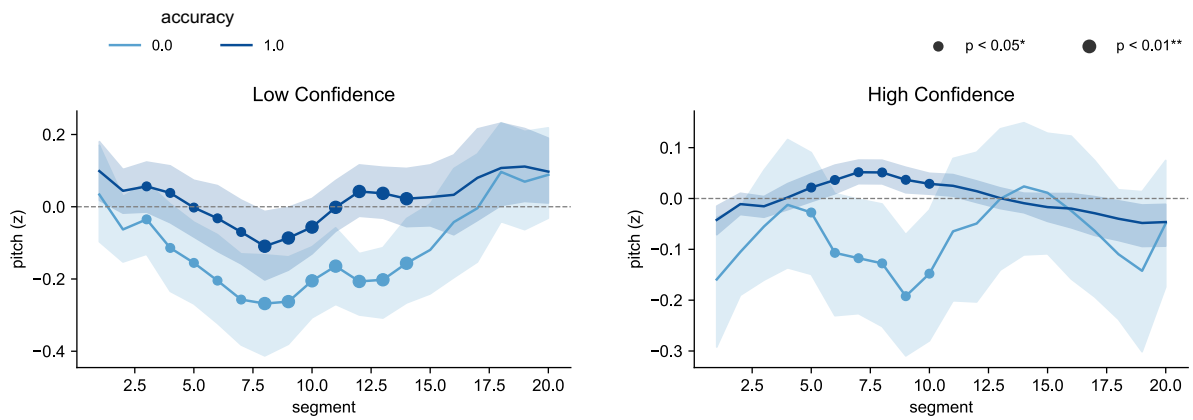
462 In order to further examine these dynamic effects, we identified significant clusters in participant's
463 intonation by running a permutation test on the differences between confident and doubtful utterances (see
464 methods). There were two significant clusters: the first one corresponded to segments 5 to 11 (p = 0.008) and
465 the second one to segments 16 to 20 (p = 0.036, see Figure 2). To examine which underlying variables (SOA,
466 accuracy or confidence) predicted pitch in these two temporal windows, we ran hierarchical regressions in the
467 two clusters separately.

468 In the first time window, we found that – as expected – there was a highly significant effect of
469 confidence (beta = 0.08 +/- 0.02 se, t = 4.2, p < 0.001) on pitch, but there was also a main effect of accuracy
470 (beta = 0.06 +/- 0.025 se, t = 2.4, p = 0.016) and an interaction between confidence and accuracy (beta = -0.05

471 +/- 0.02 se, $t = -2.4$, $p = 0.015$), while the effect of SOA was not significant when entering all three variables
472 in the model ($\beta = 0.0003$ +/- 0.0002 se, $t = 1.27$, $p = 0.2$). In addition, a mediation analysis revealed that the
473 effect of confidence on pitch was mediated at 12% (95% ci [-0.07, 0.30]) by accuracy in this temporal window,
474 which was not significantly different from chance level ($p = 0.18$). Confidence still had a significant direct
475 effect after taking this mediation into account ($p < 0.001$). Conversely, the effect of accuracy on pitch was
476 partially mediated by confidence (38%, 95% ci [0.23, 0.61], $p < 0.001$), but was still significant after taking
477 this mediation into account ($p < 0.001$). In the second time window, there was a main effect of confidence
478 ($\beta = -0.03$ +/- 0.01 se, $t = -3$, $p = 0.002$), but no effects of SOA ($p > 0.7$) nor accuracy ($p > 0.8$), and SOA
479 and accuracy did not mediate the effect of confidence on pitch ($p > 0.7$). Thus, in the beginning of the word,
480 pitch was determined by a mixture of sensory evidence, accuracy and confidence; however, it depended
481 exclusively on confidence towards the end of the word.

482 Strikingly, the interaction between confidence and accuracy reflected the fact that, when examining
483 separately high and low confidence trials, intonation still reflected accuracy (Figure 3; see also Figure S3 for
484 a detail of the four levels of confidence). In particular, when participants reported being confident in their
485 responses, their pitch was still higher in correct trials than in incorrect trials in a temporal window ranging
486 from the 5th to the 10th segment (see Figure 3). Similarly, when participants reported low confidence, their pitch
487 was still higher in correct trials as compared to incorrect trials in a temporal window ranging from the 3rd to
488 the 14th segment (corresponding to two successive significant clusters ranging from the 3rd to the 7th and 8th to
489 the 14th segment). This analysis shows that speakers' accuracy is still manifested in their intonation, over and
490 beyond their own metacognitive awareness.

491



492

493 **Figure 3. Intonational profiles depending on accuracy and confidence.** Normalized pitch is shown separately for low (left) versus
 494 high (right) confidence, and accurate (dark blue) and inaccurate trials (light blue). Markers' sizes show significant clusters identified
 495 by running a permutation test on the differences between accurate and inaccurate responses in low and high confidence trials
 496 separately ($p < 0.05$: small circles; $p < 0.01$: big circles). For low confidence responses, the permutation test revealed two significant
 497 clusters: the first one ranging from the 3rd to the 7th segment ($p = 0.04$), and the second ranging from the 8th to the 14th segment $p =$
 498 0.005). For high confidence responses, the permutation test revealed one significant cluster ($p = 0.013$) from the 5th to the 10th segment.
 499 Shaded areas show the 95% confidence intervals.

500

501 **3.4. Subjective confidence and objective accuracy can be extracted from speech prosody algorithmically**

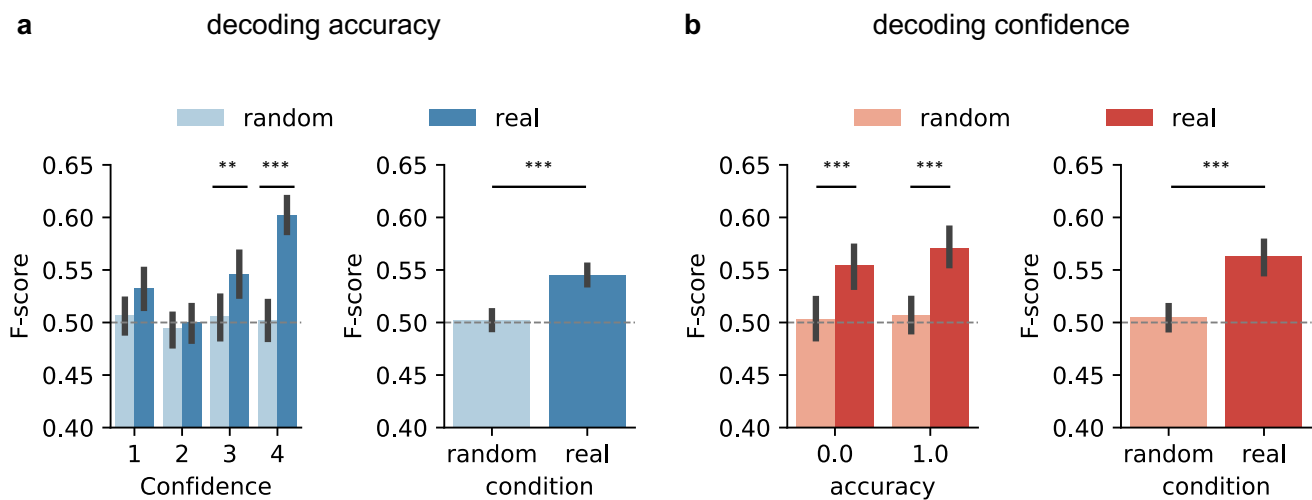
502 To further examine this dissociation, we used automatic classification algorithms to test whether
 503 speakers' accuracy and confidence can be decoded separately from the pitch, loudness and duration of their
 504 voice (see methods). We found that both accuracy and confidence could be separately decoded from this
 505 information only (see Figure 4 and S4).

506 Machine classifiers were able to detect speakers' accuracy with a performance of 60.2% (SD = 3.7)
 507 when they reported being 'fully confident' (rating of 4), and with a performance of 54.6 % (SD = 4.4) when
 508 they reported being 'confident' (rating of 3). By contrast, the accuracy of the speaker could not be reliably
 509 decoded for low levels of confidence: classification performance only reached 53.2% (SD = 4) for the lowest
 510 level of confidence, and 50% (SD = 3.8; $p = 0.5$) for the second level of confidence. To assess the significance
 511 of this result, these classification performances in decoding accuracy were compared with classification
 512 performances obtained with randomly permuted data (Ojala & Garriga, 2010). A rmANOVA with the
 513 accuracy of the classifications as a dependent variable, and confidence (four levels) and dataset (real vs.
 514 permuted) as independent variables, revealed a main effect of confidence ($F(1,19) = 22.5$, $p < 0.001$, $\eta p^2 =$
 515 0.33), a main effect of dataset ($F(1,19) = 58.51$, $p < 0.001$, $\eta p^2 = 0.52$) and a significant interaction ($F(1,19)$

516 = 40.81, $p < 0.001$, $\eta^2 = 0.33$). This interaction reflected the fact that classification performances in decoding
517 a speaker's accuracy were significantly higher than the chance-level estimated in the permuted dataset when
518 participants were confident (post-hoc Tukey HSD with FDR correction, confidence = 4: $p < 0.001$; confidence
519 = 3, $p = 0.004$), but only marginally so for the lowest level of confidence (confidence = 1: $p = 0.07$) and not
520 significantly so for the second level (confidence = 2, $p = 0.78$).

521 The confidence of the speaker could also be decoded above chance, with a performance of 55.4% in
522 incorrect trials (SD = 4.4), and 57.1% (SD = 3.8) in correct trials. A rmANOVA with classification
523 performances as a dependent variable, and accuracy (two levels) and dataset (real vs. permuted) as independent
524 variables, revealed a main effect of dataset ($F(1,19) = 60.95$, $p < 0.001$, $\eta^2 = 0.48$), no effect of accuracy
525 ($F(1,19) = 2.43$, $p = 0.14$, $\eta^2 = 0.03$) and no interaction ($F(1,19) = 0.4$, $p = 0.54$, $\eta^2 = 0.01$). Classification
526 performances in decoding speakers' confidence were significantly higher than the chance-level estimated in
527 the permuted dataset both when participants were accurate (post-hoc Tukey HSD with FDR correction, $p <$
528 0.001), and when they were inaccurate ($p < 0.001$).

529 Overall, this analysis confirms that the intonation, loudness and duration of a spoken utterance
530 separately reflect accuracy and confidence, since both constructs could be decoded automatically, across all
531 conditions in the case of confidence, and in a subset of the data (i.e., high confidence responses) for accuracy.
532 Note that an alternative classification method (support vector machines) lead to essentially the same
533 conclusions (see Figure S4).



534

535 **Figure 4. Results of the k-nearest-neighbors classification. A) Classifiers' performances in decoding objective accuracy for**
 536 **each level of confidence (left), and overall (right).** To examine whether speech prosody contains enough information to
 537 automatically infer a speaker's accuracy, we relied on a 5-fold cross-validation k-nearest neighbors (kNN) classification procedure.
 538 Over 20 independent iterations, a balanced subset of the data was selected pseudo-randomly from the full dataset for each levels of
 539 confidence, and divided into five folds containing 50% of correct trials, and 50% of incorrect trials (see methods for full details).
 540 One of the folds served as a "test set", and the four other fold served as a "training test". For each items of the test set, the Euclidean
 541 distance between the pitch and loudness profiles of this item, and the pitch and loudness profiles of each of the items of the training
 542 test, was computed. For duration, a simple difference was computed. For each acoustic dimension, the 5 training test items with the
 543 smallest distance to the test item were identified. The supposed accuracy of the test item was then classified as the most frequent
 544 class amongst these fifteen nearest neighbors (five for each acoustic dimension). Finally, the classifier's performance was estimated
 545 by computing an F-value, which is the harmonic mean of the recall and precision of the classifier (see methods). We present the F-
 546 values averaged across the 20 repetitions. Bar plots show the average performances of the classifier for real (darker shades) and
 547 permuted (lighter shades) data, with error bars showing the 95% confidence intervals estimated over the 20 repetitions. Dashed lines
 548 show the theoretical chance-level (50%, black). Asterisks show the results of the post-hoc Tukey HSD with FDR correction
 549 comparing real and permuted data allowing to estimate chance-level (see methods), with * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
 550 (exact p-values are reported in the main text). The chance-level estimated with permuted data was 50.2% overall (SD = 2; confidence
 551 = 1: 50.7% (3.5); confidence = 2: 49.5% (3.3); confidence = 3: 50.6% (4.6); confidence = 4: 50.2% (4.2)). The performance of the
 552 classifier over all confidence levels was 54.5% (SD = 2), which was highly significantly above chance level ($t(19) = 7.65$, $p < 0.001$).
 553 **B) Classifiers' performances in decoding subjective confidence for each level of accuracy (left) and overall (right).** To assess
 554 whether speech prosody contains enough information to infer a speaker's level of confidence, we applied the same method, now
 555 decoding binary confidence (High vs. Low) for each level of accuracy and SOA (see methods). The chance-level estimated with
 556 permuted data was 50.3% (SD = 4.2) for incorrect trials, 50.7 (3.5) for correct trials, and 50.5 (2.6) overall. The performance of the
 557 classifier over all accuracy levels was 56.3% (SD = 3.5), which was highly significantly above chance level ($t(19) = 7.81$, $p < 0.001$).

558

559 **3.5. Impact of competence, confidence bias and metacognitive sensitivity on prosodic signatures of**
 560 **confidence.**

561 Finally, we wanted to assess whether participants' ability to perform the task (their competence), their
 562 general tendency to be confident (their confidence bias), and their global ability to evaluate their performances
 563 (their metacognitive sensitivity) related to how accuracy and confidence were automatically reflected in their
 564 voice. If epistemic prosody constitutes an adaptive mechanism allowing listeners to filter information coming

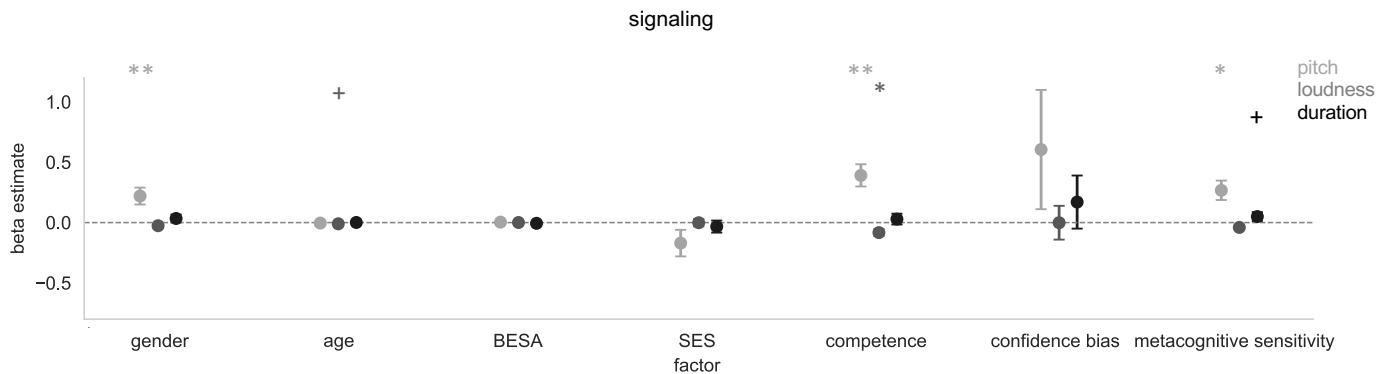
565 from unreliable social partners, we may expect that vocal signatures of accuracy and confidence may be more
566 manifest in competent (or meta-competent) speakers.

567 To test this idea, we computed for each participant their global performances (mean d' over all trials,
568 reflecting how competent they were in the perceptual task), their confidence bias (mean confidence over all
569 trials corrected for performances, see methods), and their metacognitive sensitivity (approximated through
570 meta- d' , a measure that reflects how well participants confidence judgements' track their performance,
571 independently of their general biases to be more or less confident, see methods and Fleming, 2017). We then
572 examined how these measures related to signaling (after controlling for several other individual factors, see
573 below), by computing three metrics that reflected the extent to which confidence and accuracy affected pitch,
574 loudness and duration.

575 For pitch, we quantified this difference by taking the Euclidean distance between pitch profiles
576 extracted from high versus low confidence (or correct versus incorrect) responses for each participant. For
577 loudness and duration, we computed the mean difference between high (or correct) and low confidence (or
578 incorrect) trials. Three linear regressions including global performance, confidence bias, metacognitive
579 sensitivity, as well as several individual factors (gender, age, socioeconomic status, and empathic traits, see
580 methods), and interactions between these factors and signaling type (accuracy or confidence) were then
581 conducted separately for each acoustic dimension (see methods for the exact formula).

582 As can be seen in Figure 5, after controlling for all other factors, competence significantly predicted
583 higher intonational signaling (beta = 0.39 +/- 0.09 se, $t = 4.27$, Bonferroni corrected $p = 0.002$), with no
584 significant interaction with the type of signaling (i.e., accuracy or confidence, $p > 0.6$). When all other factors
585 including competence were considered, metacognitive sensitivity also significantly predicted increased
586 intonational signaling (beta = 0.28 +/- 0.08 se, $t = 3.32$, $p = 0.049$, here again with no significant interaction
587 with the type of signaling, $p > 0.2$), and it also marginally increased signaling at the level of duration (beta =
588 0.05 +/- 0.04 se, $t = 1.315$, $p = 0.053$). Thus, speakers' level of competence and metacognitive sensitivity in
589 the task increased their signaling of both confidence and competence. By contrast, there were no significant

590 associations between confidence bias and any of the acoustic dimensions (all p-values > 0.1), which suggests
 591 that individuals did not display signs of competence or confidence more or less saliently depending on their
 592 metacognitive bias (see Figure 5 and supplementary results for details about additional effects of loudness,
 593 age and gender).



594

595 **Figure 5. Signaling depending on individual factors.** Regression analysis were conducted on each acoustic dimension separately
 596 to assess the impact of individual traits on signaling. Signaling for pitch corresponded to the Euclidean distance between intonational
 597 profiles computed for high confidence (or correct responses) minus low confidence (or incorrect) responses. Signaling for loudness
 598 and duration were computed similarly, but using average values rather than time series. Given that no interactions were observed
 599 between factors and type of signaling (accuracy and confidence), we show combined effects. We present beta estimates, with error
 600 bars corresponding to standard errors. + represents Bonferroni corrected $p < 0.06$; * $p < 0.05$ and ** $p < 0.01$ for the statistical
 601 significance of each factor in the three (one for each acoustic dimension) linear regressions.

602

603

604 4. Discussion

605

606 We find that, even in the absence of an audience, speech prosody automatically and separately reflects
 607 speakers' confidence and accuracy. This finding shows that the subjective confidence and objective
 608 competence of speakers are naturally manifested in on aspect of their behavior, thus potentially providing a
 609 low-level, cheap mechanism for detecting whether the information they are communicating should be trusted
 610 or not.

611 Our results reveal that intonation, loudness and duration differently reflect the underlying
 612 psychological processes leading to the production of a verbal response. While duration and intonation reflect
 613 confidence per se, loudness appears to be mostly driven by cognition (i.e., accuracy) rather than metacognition

614 (i.e., confidence). By revealing that various aspects of prosody are associated with different underlying
615 psychological processes, these results go beyond previous research showing simple associations between
616 speech and confidence, without assessing the impact and potentially mediating role of sensory evidence or
617 accuracy.

618 Some aspects of epistemic prosody were not systematically linked to cognitive aspects presumably
619 associated with fluency, such as sensory evidence and accuracy, but rather, truly reflected subjective aspects
620 of experience linked to metacognition (i.e., the subjective perception of such fluency, Ackerman & Zalmanov,
621 2012; Proust, 2012). In particular, intonation was impacted by sensory evidence and accuracy early in the
622 word, while towards the end of the word it was exclusively determined by subjective confidence. Thus, this
623 specific intonation pattern, in which pitch falls at the end of the word, naturally means that the speaker is
624 confident: it is tightly linked to confidence reports per se, and present even when speakers have no deliberate
625 intention to produce it. Interestingly, this intonation pattern finely overlaps with listeners mental
626 representations about confident prosodies uncovered with a data driven method (Goupil et al., 2020), which is
627 in line with our hypothesis that epistemic prosody supports a low-level adaptive mechanism of epistemic
628 vigilance, with concurrent adaptations on the side of both senders and receivers.

629 Another interesting aspect of this result concerns timing. Intonation was found to reflect the
630 chronometry of the mental processes used to produce an utterance: cognition is reflected in intonation before
631 metacognition, just like it is in neural signals where correlates of perceptual and decisional processes are
632 observable several hundreds of milliseconds before neural correlates of metacognitive processes (Fleming &
633 Dolan, 2012). This sequence of events is thought to reflect the fact that metacognition, supported by pre-frontal
634 regions (Bang & Fleming, 2018; Cortese et al., 2016), relies on the integration of several sources of
635 information coming from downstream associative and perceptual areas. As such, our results are compatible
636 with the idea that the subjective confidence expressed in explicit reports results from inferential processes that
637 incorporate various sources of information, over and beyond processes and representations directly responsible
638 for decisions (Fleming & Daw, 2017; Koriat, 2012; Proust, 2012).

639 We also find that other acoustic features previously associated with confidence in the literature, such
640 as loudness, are actually not systematically linked to confidence per se, but rather, reflect the speaker's
641 underlying accuracy. Thus, beyond offering a window into speakers' confidence, speech prosody also directly
642 provides information about competence. Consistent with this idea, we also found that accuracy can be decoded
643 from prosody over and beyond confidence (Figure 4). Further research should investigate whether - as is the
644 case for confidence (Goupil et al., 2020; Jiang & Pell, 2017) - listeners are actually able to exploit these
645 prosodic signatures to infer the accuracy of a speaker. This could be particularly important given the fact that
646 explicit confidence reports are highly prone to biases (Moore & Healy, 2008), so being able to infer
647 interlocutor's competence directly (i.e., without relying on their metacognitive evaluations of confidence)
648 could be a highly adaptive solution. Notably, individuals' tendency to display their accuracy and confidence
649 in speech prosody was not related to their confidence bias (Figure 5). Thus, compared to explicit (verbal)
650 reports, which are highly prone to metacognitive biases, speech prosody may provide a better proxy to
651 competence, and be less misleading to infer whether a speaker is actually right or wrong, in particular when
652 interacting with individuals that have an overconfident (Moore & Healy, 2008; Zarnoth & Sniezek, 1997) or
653 underconfident bias (Björkman, Juslin, & Winman, 1993; Scheck & Nelson, 2005).

654 We also find that epistemic prosody is increased in individuals who are more competent and, to a lesser
655 extent, in individuals who have higher metacognitive sensitivity (after controlling for the impact of accuracy).
656 Thus, individuals who are proficient in a task manifest their confidence in speech prosody more than others,
657 even in the absence of social partners. This is consistent with the idea that epistemic prosody serves an adaptive
658 function, enabling listeners to infer truth and certainties from proficient partners.

659 Finally, the fact that such epistemic prosodic markers were observed in the absence of an audience is
660 consistent with past research (Kimble & Seidel, 1991), and shows that they are manifested constitutively and
661 automatically as a function of the speaker's level of confidence and accuracy: i.e., they constitute natural signs
662 of confidence and competence. This is not to say that these displays are never under voluntary control: humans
663 can obviously control the pitch, duration and volume of their voice, making it possible to deliberately use

664 prosodic displays as "social tools" during conversation (Crivelli & Fridlund, 2018; Van Zant & Berger, 2019;
665 Wharton, 2009) and past research has shown that, indeed, similar prosodic signatures as the ones we find here
666 are exploited during communicative interactions: listeners perceive them to infer confidence and honesty in
667 their partners (Goupil et al., 2020; Jiang & Pell, 2017), and speakers manipulate them in order to persuade
668 their interlocutors (Van Zant & Berger, 2019). Thus, it will be important to extend our psychophysical
669 approach to social interactions in future work, for instance by relying on dyadic collective decision-making
670 paradigms (Bahrami et al., 2010; Fusaroli et al., 2012; Pescetelli & Yeung, 2020), in order to examine how
671 specific social settings - such as the fact that the speaker is engaged in a cooperative or competitive interaction
672 - impact how speakers display these prosodic signatures. A particularly interesting question is whether
673 speakers manipulate all prosodic features (intonation, accentuation, global levels of pitch or loudness,
674 duration), or only some of them (e.g., global levels of loudness and pitch, but not intonation). Another open
675 question is how variations in physical attributes (e.g., body size) and social traits (e.g., social dominance)
676 would modulate and interact with the relationships we found here between prosodic signaling and
677 (meta)competence.

678 Beyond vocal communication, this result is to our knowledge, the first experimental demonstration
679 that distinct features of a single observable behavior can reflect accuracy and confidence sequentially, and
680 distinctively. Because accuracy and confidence typically correlate, there is considerable debate concerning
681 whether or not confidence reduces to objective aspects of the decision-making process (Carruthers, 2016;
682 Kiani & Shadlen, 2009) or rather, is tied to higher-order, integrative processes (Fleming & Daw, 2017; Koriat,
683 2012; Moulin & Souchay, 2015). In favor of the second hypothesis, dissociations between objective accuracy
684 and subjective confidence have been observed at the level of the brain (Bang & Fleming, 2018; Cortese et al.,
685 2016), but whether this dissociation can also be manifested in overt behaviors, such as response time (Patel et
686 al., 2012) or post-decision persistence, remained unclear (e.g., see Insabato et al., 2016 vs. Kepecs et al., 2008
687 for debates concerning animals; Gliga & Southgate, 2016 vs. Goupil & Kouider, 2016 concerning preverbal
688 children). By showing that decision-making and metacognition have different manifestations at the level of a

689 socially-observable behavior like speech prosody, our results therefore make a key theoretical contribution in
690 support of distinguishing confidence from decision-making processes.

691

692

693 **5. Conclusions**

694

695 In this study, we show that individuals truly and automatically display their subjective confidence in
696 the absence of an audience, and thus, without the necessary involvement of voluntary control and
697 communicative intentions. Further research could examine whether this behavioral signature can be used to
698 assess subjective confidence in pre-verbal populations (Goupil & Kouider, 2016), to discriminate confidence
699 from accuracy in the context of forensic practices or witness testimonies (Tenney, MacCoun, Spellman, &
700 Hastie, 2007), improve epistemic vigilance during linguistic interactions to limit the spread of fake news
701 (Lazer et al., 2018), or as a diagnostic tool, given that explicit metacognition appears to be specifically linked
702 to psychiatric symptoms, over and beyond the impact of task performances (Rouault, Seow, Gillan, & Fleming,
703 2018). Beyond confidence, the present methodology of “event-related prosody”, which combines a
704 psychophysical task with single-trial acoustic analysis, opens new avenues to investigate how subjective
705 mental states are related to speech prosody. For instance, it is generally assumed that emotional feelings such
706 as happiness and sadness can be directly perceived from the voice (Juslin & Laukka, 2003), but it remains
707 unclear whether we can truly and directly perceive feelings from prosody, rather than inferring them indirectly
708 through the perception of physiological changes typically associated with these feelings (Barrett, 2017;
709 Galvez-Pol, Salome, Li, & Kilner, 2020).

710

711

712 **References**

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897

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904

905 **Authors contributions.** L.G., and J.J.A. designed the experiment. L.G. collected, and analyzed the data. L.G.
906 wrote the paper with comments from J.J.A.

907

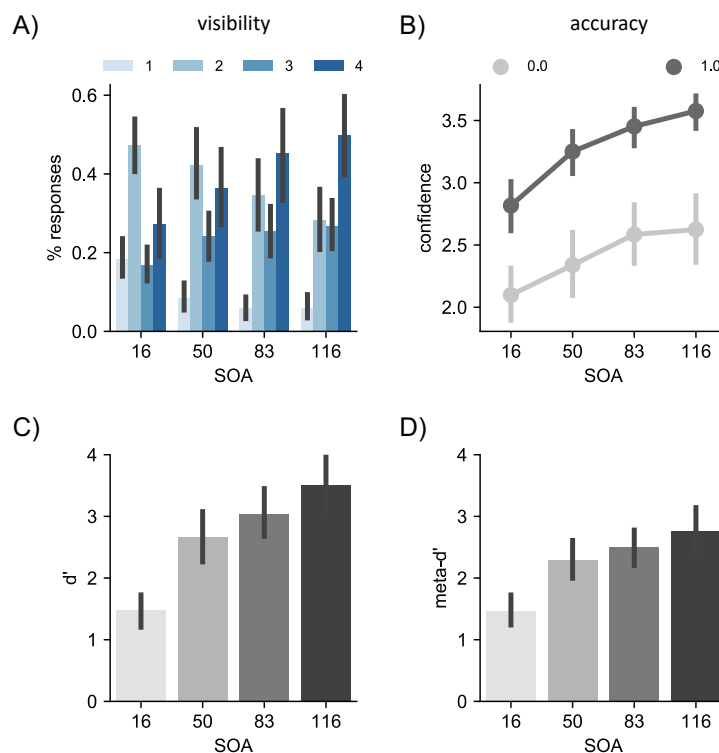
908 **Competing interests.** The authors declare that there is no conflict of interest regarding the publication of this
909 article.

910

911 Supplementary Materials

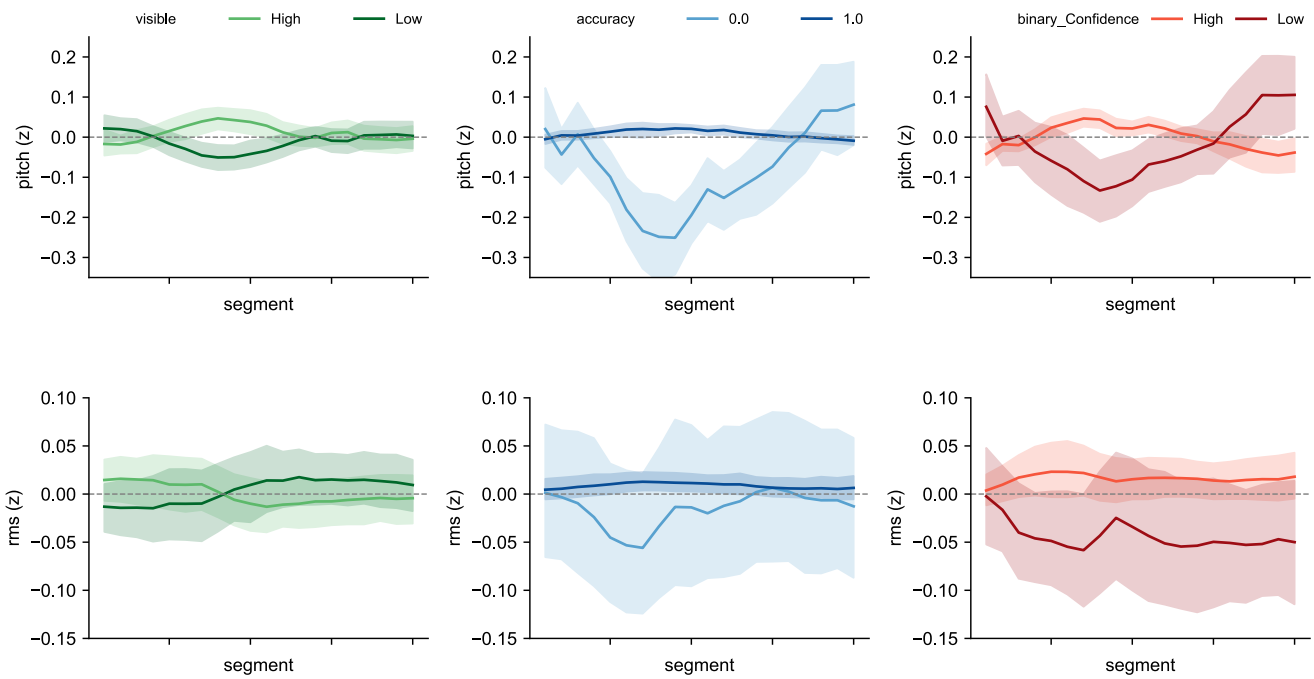
912

913 **Behavioral results.** As expected from previous research relying on similar visual paradigms (Charles et al., 2013;
914 Kunimoto et al., 2001; Rausch et al., 2018), both visibility ($F(1,39) = 103, p < 0.001, \eta^2 = 0.72$), sensitivity (i.e., d' ,
915 $F(1,39) = 169, p < 0.001, \eta^2 = 0.81$) and confidence ($F(1,39) = 116, p < 0.001, \eta^2 = 0.74$) increased with SOA. As
916 can be seen in Figure S1.A. below, at the shortest SOA participants rarely reported not seeing anything at all, but often
917 reported seeing only a glimpse of the stimulus. Also of note is the fact that sensitivity (d') remained above chance level
918 even for the shortest SOA ($M = 1.48 \pm 0.8, t(39) = 7.7, p < 0.001$) but not for unseen stimuli ($M = 0.84 \pm 2.41, t(39)$
919 $= 0.87, p = 0.38$). This pattern of result contrasts with previous findings showing that objective performances can be
920 better than chance even for unseen stimuli (Charles et al., 2013; Kunimoto et al., 2001). This could be due to the fact
921 that we rely on verbal reports here, rather than less ecological task involving poorly demanding motor responses such
922 as button presses.



923

924 **Figure S1. Behavioral results. A) Visibility ratings depending on SOA.** The percentage of trials was computed for
925 each level of visibility depending on SOA, and averaged across participants. B) Confidence was averaged for each
926 participant depending on accuracy. B) Sensitivity (d') was computed for each SOA. D) Metacognitive sensitivity
927 (meta- d') was computed for each SOA. Error bars show the 95% confidence interval.

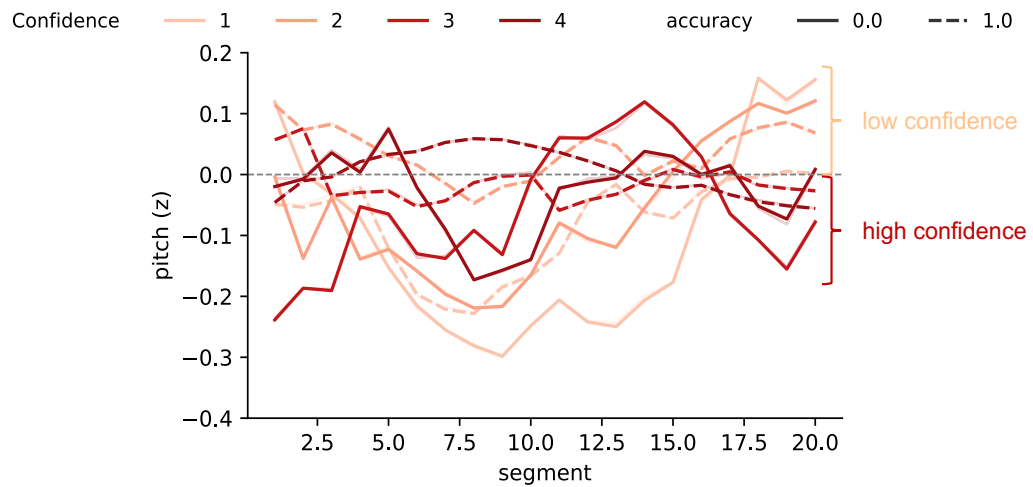


928

929 **Figure S2.** Normalized pitch (top) and RMS (bottom) are shown for each segment, depending on SOA (left / green, low:
 930 16 and 50ms versus high: 83 and 116ms), accuracy (middle / blue) and confidence (right / red). Error bar show the 95%
 931 confidence intervals.

932

933



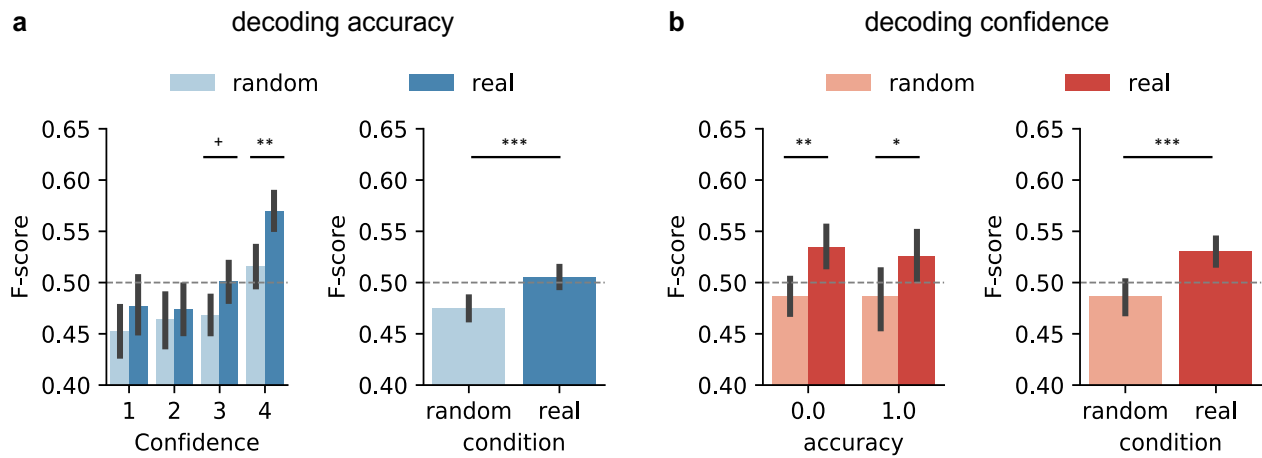
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935

936 **Figure S3.** Normalized pitch is shown separately for each level of confidence and accurate (dashed lines) and
 937 inaccurate trials (plain lines).

938

939



940

941 **Figure S4. Results of the support-vector machines classification. A) Decoding objective accuracy.** The same
 942 analysis presented in Figure 4 was repeated with an alternative classification procedure (support vector machines,
 943 SVMs). We present the F-values averaged across the 20 repetitions. Bar plots show the average performances of the
 944 classifier for real (darker shades) and permuted (lighter shades) data, with error bars showing the 95% confidence
 945 intervals estimated over the 20 repetitions. The chance-level estimated with permuted data (see methods) was 47.5%
 946 (SD = 2.6) overall (confidence = 1: 45.2 (5.7); confidence = 2: 46.4% (5.8); confidence = 3: 46.8% (4); confidence = 4:
 947 51.5% (4.4)). The performance of the classifier over all confidence levels was 50.5% (SD = 2.3), which was highly
 948 significantly above the chance level estimated with permuted data ($t(19) = 5.58, p < 0.001$). As for KNNs, a rmANOVA
 949 revealed a significant main effect of condition (real vs. permuted, $F(1,19) = 31.2, p < 0.001, \eta^2 = 0.27$), and a main
 950 effect of confidence ($F(1,19) = 47.4, p < 0.001, \eta^2 = 0.53$) and a marginal interaction between the two factors ($F(1,19)$
 951 $= 3.3, p = 0.08, \eta^2 = 0.053$). Performances were higher in the dataset as compared to permuted data when participants
 952 were highly confident (confidence 4: $p = 0.002$, post-hoc Tukey HSD with FDR correction), but only marginally so for
 953 confidence = 3 ($p = 0.068$), and not significantly so for lower levels of confidence (confidence 1: $p = 0.17$; confidence
 954 2: $p = 0.62$). Asterisks show the results of the post-hoc Tukey HSD with FDR correction comparing classification
 955 performances with the chance-level estimated with permuted data, with + $p < 0.07$, * $p < 0.05$, ** $p < 0.01$, *** $p <$
 956 0.001 (see main text for exact p-values). Dashed lines show the theoretical chance-level (50%, black). **B) Decoding**
 957 **subjective confidence.** To assess whether speech prosody contains enough information to infer a speaker's level of
 958 confidence, we applied the same method, now decoding binary confidence (High vs. Low) for each level of accuracy
 959 and SOA (see methods). The chance-level estimated with permuted data was 48.7.3% (SD = 3.9) for incorrect trials,
 960 48.6 (6.3) for correct trials, and 48.6 (3.5) overall. The performance of the classifier over all accuracy levels was 53%
 961 (SD = 2.9), which was highly significantly above chance level ($t(19) = 6.9, p < 0.001$). As for KNNs, a rmANOVA
 962 revealed a significant main effect of condition (real vs. permuted, $F(1,19) = 47.74, p < 0.001, \eta^2 = 0.21$), no effect of
 963 accuracy ($F(1,19) = 0.08, p = 0.76, \eta^2 = 0.003$) and no interaction ($F(1,19) = 0.29, p = 0.59, \eta^2 = 0.002$). Performances
 964 were higher in the dataset as compared to permuted data for both levels of accuracy (correct: $p = 0.02$; incorrect $p =$
 965 0.006 ; post-hoc Tukey HSD with FDR correction).

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968 **Relationship between individual factors and signaling.**

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971 Beyond the effects related to our main claims reported in the manuscript, we also observed that, at the level of loudness,
 972 competence significantly decreased signaling ($\beta = -0.08 \pm 0.03 \text{ se}, t = -2.94, p = 0.014$), mirroring the positive
 973 impact observed for duration (there was a negative correlation between loudness signaling and duration signaling: ρ
 974 $= -0.35, p = 0.026$; and more generally between duration and volume, participants spoke louder when they responded

975 faster overall, $\rho = -0.27$, $p < 0.001$). Age also marginally decreased signaling at the level of loudness (beta = $-0.01 \pm$
976 0.006 se, $t = -1.75$, $p = 0.056$), but this impact of age is difficult to interpret given the short range included in our study
977 (18- to 30-year-olds). Finally, gender was significantly associated with intonational signaling (beta = 0.22 ± 0.07 se, t
978 $= 3.1$, $p = 0.003$, all other comparisons were not significant), reflecting the fact that intonational variations were stronger
979 in males as compared to females. This could be consistent with previous reports suggesting substantial differences in
980 men and women regarding subjective confidence reports (Lundeberg, Fox, & Puncoha, 1994), but is more likely to be
981 due to general gender differences in the range of pitch variations (Elliott & Theunissen, 2009; Henton, 1989).