



HAL
open science

The effect of speech degradation on the ability to track and predict turn structure in conversation

Céline Hidalgo, Isaīh Mohamed, Christelle Zielinski, Daniele Schön

► **To cite this version:**

Céline Hidalgo, Isaīh Mohamed, Christelle Zielinski, Daniele Schön. The effect of speech degradation on the ability to track and predict turn structure in conversation. *Cortex*, 2022, 151, pp.105-115. <10.1016/j.cortex.2022.01.020>. <hal-03823231>

HAL Id: hal-03823231

<https://hal.science/hal-03823231v1>

Submitted on 20 Oct 2022

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire HAL, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



HAL Authorization

1 **Title:** The effect of speech degradation on the ability to track and predict turn structure in
2 conversation

3 Céline Hidalgo¹, Isaiïh Mohamed¹, Christelle Zielinski², Daniele Schön¹

4 ¹ Aix Marseille Univ, Inserm, INS, Inst Neurosci Syst, Marseille, France

5 ² Aix-Marseille Univ, Institute of Language, Communication and the Brain, France

6 **Corresponding author:** Céline Hidalgo, celine.hidalgo@univ-amu.fr

7 **Professional Address:** Institut de Neurosciences des Systèmes, Faculté de Médecine, bd Jean
8 Moulin, 13005 Marseille, France

9 **Telephone:** 04 91 32 41 02

10

11 **Abstract**

12 Conversation represents a considerable amount of the daily language usage and plays an
13 important role in language acquisition. In conversation, listeners simultaneously process
14 their interlocutor's turn and prepare their own next turn. As such the turn-taking dynamics
15 heavily **relies** on prediction. In other words, listeners avail prior knowledge to constrain both
16 speech perception and production. Here we explored the relation between prediction and
17 comprehension while watching two interlocutors having a conversation. We capitalize on
18 gaze switch as a proxy of predictive behaviour to class dialogue turns as more or less well
19 predicted and explore how this affects dialogue comprehension. Moreover, we study the
20 extent to which speech degradation, by increasing the global uncertainty of the context,
21 affects the relation between predictions, brain correlates of prediction errors (N400) and

22 global comprehension. Results show that 1) listeners direct gaze to the current speaker, in
23 particular in challenging conditions, 2) gaze behaviour possibly affects the semantic
24 processing of the upcoming turn (N400), 3) participants with a more efficient gaze predictive
25 behaviour better solve semantic uncertainties at the turn onset, in particular in the most
26 challenging listening condition. Our findings contribute to a better understanding of the
27 relation between predictions, neural predictions errors and speech comprehension under
28 challenging conditions.

29 **Keywords:** conversation, ERPs, eye-tracking, prediction, turn-taking.

30

31 **Author contributions:** Conceptualization C.H. and D.S.; Data curation C.H., C.Z. and I.M.;
32 Formal Analysis C.H.; Funding acquisition D.S.; Project administration C.H.; Supervision D.S.;
33 Visualization C.H, C.Z. and I.M; Writing – original draft C.H., I.M., C.Z. and D.S.

34

35 **Author Note:** In accordance with the Peer Reviewers' Openness Initiative
36 (<https://opennessinitiative.org>, Morey, Chambers, Etchells, Harris, Hoekstra, Lakens, et al.,
37 2016), all materials and scripts associated with this manuscript are available on
38 <https://osf.io/7dc6y/>

39 Introduction

40 Speech perception is not the result of a real-time decoding of audio-visual information. It is a
41 dynamic process of an anticipatory nature building on 1) the use of the linguistic and extra-
42 linguistic context to generate hypotheses about the upcoming signal, i.e. we make
43 predictions about what we are likely to hear and 2) a comparison of our predictions against
44 what is actually perceived. Thus, when we listen to a conversation between two people, we
45 anticipate, for example, the words that the speakers will produce according to the linguistic
46 context that precedes their utterances. The more we know about this context, the fewer
47 prediction errors we make and the faster and more accurate our understanding of their
48 conversation. According to predictive coding theory (Clark, 2013), predictions would indeed
49 be a default brain mode of operation for processing sensory information (Friston, 2005). To
50 optimize speech perception, the brain would pre-activate representations of the expected
51 speech input (Molinaro et al., 2016) at a phonological, lexical, semantic or even syntactic
52 level (Pickering & Gambi, 2018). With increasingly accurate predictions, the brain would only
53 need to compute the difference between sensory input and prediction, thereby decreasing
54 the cost of perceptual processing and speeding up the understanding of the spoken
55 message. A well-known fact in the comprehension literature is that the amount of
56 contextual information, i.e. the increase in the precision of prediction, positively influences
57 the speed of word recognition (Tyler & Wessels, 1983). This has been thoroughly studied
58 using event-related potentials, by observing changes in the amplitude of a negative
59 component. Indeed, words with low cloze probability engender a prediction error that is
60 visible in an increase of the N400 amplitude. By contrast the N400 amplitude is reduced
61 when perceiving speech in highly predictive contexts (see for a review Kutas & Federmeier
62 2011). However, until now, no study had shown a direct link between contextual predictions

63 and the integration of these predictions in the semantic comprehension process in a
64 conversational context. This is due to the fact that, while prediction errors engender
65 observable brain responses (e.g., N400 or Mismatch Negativity), this is not the case of
66 predictions. Recently, Grisoni and colleagues (Grisoni et al., 2021) described an
67 electrophysiological index of predictions called the "Semantic Prediction Potential", and
68 showed, by measuring the N400 brain response during the perception of more or less
69 contextually constrained sentences, the direct effect of predictions (SPP) on the processing
70 of prediction errors (N400).

71 Another possibility to infer the ongoing predictions is to use behavioural measures. In the
72 case of language, several studies have used for instance eye movements during reading
73 (Rayner, 1978; Staub, 2015). Similarly, in speech perception, some authors relied on the
74 implicit anticipatory gaze behaviour when listening to different people having a conversation
75 (Casillas & Frank, 2017; Keitel et al., 2013). More precisely, listeners anticipate the end of the
76 turn of the current speaker and switch gaze to the following speaker, before the actual onset
77 of the new turn. This predictive behaviour is particularly important considering that the
78 silence separating speech turns of conversing speakers only lasts a few hundred milliseconds
79 (Levinson, 2016; Stivers et al., 2009). In considering turn-taking in conversation, predictions
80 build on several linguistic cues such as prosody (Roberts et al., 2015), lexical-semantic cues
81 (De Ruiter et al., 2006), syntactic structures (Selting, 1996) or pragmatic cues (Beňuš et al.,
82 2011). When listening to a dialogue (as a third person), a similar behaviour possibly takes
83 place via the generation of internal models, allowing a listener to anticipate in a precise
84 temporal window the speakers' turn-taking.

85 The aim of the current study is to explore the links between predictions at the turn level,
86 measured by gaze switch, and both local and global semantic processing when listening to a
87 dialogue, as indexed by N400 to turn onset and comprehension score, respectively.
88 Importantly we are interested in studying how these relations evolve when adding
89 uncertainty to the context by degrading the input signal. Indeed, degrading the acoustic
90 signal or adding noise or competing speakers, adds uncertainty and challenges speech
91 comprehension (Mattys et al., 2012; Peelle, 2018). To this aim, we asked participants to
92 watch videos of two people having a conversation manipulating different levels of speech
93 degradation. We measured eye movements to estimate predictive gaze behaviour and used
94 this measure to class turns as well predicted (early gaze switch) or poorly predicted (late
95 gaze switch). We also measured EEG and used the N400 as a marker of prediction error at
96 the turn onset and studied the extent to which this response is influenced by gaze
97 behaviour. Finally, all participants responded to several open questions at the end of each
98 dialogue, allowing estimating a global comprehension measure. Most importantly, we
99 explored the relation between these different variables as a function of speech degradation
100 and increasing uncertainty. We hypothesized that poorly predicted turns (late gaze switch)
101 would engender a larger N400 response compared to well anticipated turns (early gaze
102 switch). Importantly, this effect may change as a function of speech degradation and should
103 be reduced at high speech degradation levels when uncertainty is highest. We also
104 hypothesized that, if predictions are fully implicit and based on the understanding of the
105 dialogue, then gaze switches should behave similarly to comprehension score and decrease
106 from normal to moderately degraded and even more for highly degraded speech.

107

108 Materials and Methods

109 We report how we determined our sample size, all data exclusions, all inclusion/exclusion
110 criteria, whether inclusion/exclusion criteria were established prior to data analysis, all
111 manipulations, and all measures in the study. No part of the study procedures or analyses
112 was preregistered prior to the research being conducted.

113

114 Participants

115 Forty-eight participants (27 females) were tested after being informed of the procedure of
116 the study, which was approved by the Sud Méditerranée Ethics Committee (ID RCB: 2015-
117 A01490-49). In absence of a known effect size, the sample size was chosen as rather large
118 with respect to N400 studies (Šoškić et al., 2021). Inclusion and exclusion criteria:
119 Participants were between 18 and 62 years old (mean = 32, SD = 6 years). They were native
120 French speakers. They had normal or corrected to normal vision and normal hearing. years);
121 they had no history of speech disorder or neurological disease based on self-report. Prior the
122 experiment, the hearing thresholds were controlled using a 5dB-step custom screening
123 hearing test made in Python 3.7.9 (Expyriment version 0.10.0). Data from nine participants
124 were excluded because of noisy EEG recordings (high impedances or excessive
125 eye/movement artifacts) or track loss for long temporal windows in the eye-tracking dataset,
126 resulting in 39 participants in the final dataset.

127 Stimuli

128 We presented 6 audiovisual stimuli of ~4.5 minutes each, showing a man and a woman
129 having a conversation. The themes of the conversations differed and were joyful to maintain
130 attention during the whole duration of the dialogue. Dialogues contained on average 59

131 turns (min = 46; max = 66; see details in table 1). Turns lasted on average 3.75s (SD = 2.75)
132 and global speech rate was approximately 5Hz. 60% of these turns were
133 questions/responses adjacency pairs (min = 56 %; max = 66%) in order to elicit predictive
134 behaviours as suggested in Casillas & Frank, 2017 (Casillas & Frank, 2017). We used Final Cut
135 Pro X to set the gap duration at speakers' turn to 500ms in order to have homogeneous turn
136 conditions, allow anticipatory gaze behaviour (cf. Foulsham et al. 2010; Casillas and Frank
137 2017) and obtain equivalent EEG baseline for turn onset analyses.

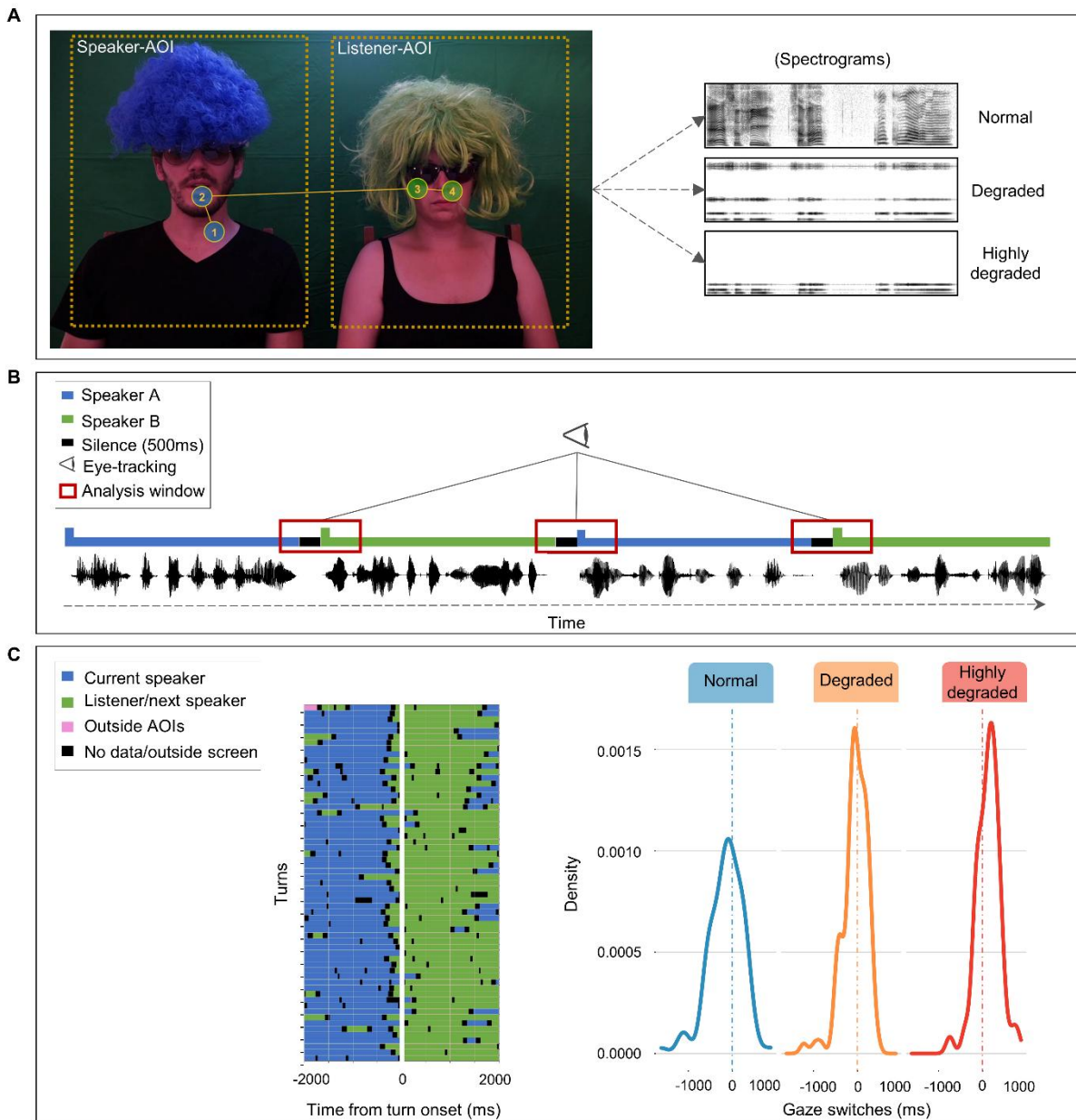
138 For the clarity of the evoked potentials, each turn onset began with a plosive consonant
139 (although we avoided bilabial to avoid visual cues preceding the plosion). In the stimuli
140 recording session, all dialogues were written and displayed on a desk in front of the speakers
141 during video shooting. Dialogues were all read by the same male and female speaker and
142 videos were recorded in an anechoic room. To avoid body movement when reading the
143 dialogues, the speakers sat on a chair and their head was maintained still by a hard hat fixed
144 to the chair. Each speaker wore sunglasses to hide eye movements and a wig to hide the
145 hard hat (Figure 1A left). Furthermore, in order to discard spurious visual cues, the non-
146 speaking speaker was "frozen" via video editing whenever a head or lip movement occurred
147 before the turn. This happened in approximately ~20% of the turns. In order to avoid sharp
148 jumps in the images of the upcoming speaker such freezing took advantage of fading and
149 morphing technics (mMorphCut plug-in ; FINAL CUT pro X).

150 In other words, turns could not be anticipated on the basis of visual information of the next
151 speaker right before the turn. Thus, anticipatory gaze behaviour cannot be interpreted in
152 response to visual cues but as auditory predictive behaviour only. We also created 12 open
153 questions for each dialogue (e.g. "why was Tom walking in the wood?") (see table 2 for more

154 examples for one dialogue). These questions were recorded using an auditory only format,
155 by a female speaker different from the one in the dialogues.

156 Speech recordings of the six dialogues were degraded using a noise vocoding approach
157 (Shannon et al. 1995; custom Matlab script). This allows to parametrically vary the spectral
158 detail, with increasing numbers of channels associated with increasing perceptual clarity
159 (Figure 1A right). The procedure allowed creating a highly degraded condition in which we
160 kept only frequency bands from 120Hz to 237Hz, 405Hz to 538Hz and 919Hz to 1028Hz (i.e.
161 3 frequency bands left with 5 ERB scales) and a moderately degraded condition in which we
162 removed all frequency bands except from 120Hz to 237Hz, from 674Hz to 805Hz, from
163 2025Hz to 2112Hz and 5208Hz to 5236Hz (so 4 frequency bands left with 8 ERB scales). The
164 overall RMS amplitude of the audio files was adjusted to be the same across all dialogues in
165 the three conditions (normal, moderately degraded, highly degraded). We also run a pilot
166 test to ensure that comprehension varied as a function of speech degradation and that, in
167 the most challenging condition, participants could still understand part of the conversation.
168 More precisely, 6 native French participants listened to audio excerpts of the dialogues and
169 repeated all words they could recognize. The excerpts were degraded in a parametric
170 manner in the number of channels, the bandwidth and the low frequency cut-off. The
171 parameters were chosen in such a way to yield a condition of moderate difficulty
172 (comprehension level between 30 and 50%) and another condition of great difficulty
173 (comprehension level between 10 and 30%).

174



175

176 Figure 1. Schematic illustration of the task and analyses. A. On the left, snapshot of the video illustrating the
 177 fixation points of the participant and the gaze switch. On the right, the three different speech conditions with
 178 normal, moderately degraded and highly degraded speech (using a vocoding approach). B. Schematic
 179 illustration of the turns in the dialogue, the controlled gap between turns (500ms) and the gaze switch window
 180 of analysis. C. On the left, gaze behaviour of a single participant showing the gaze switch for every turn of a
 181 single dialogue in the normal speech condition with respect to turn onset (zero). On the right, the gaze switch
 182 distribution for a single participant in the three different degradation conditions. A median split is used to class
 183 turns as being more or less well anticipated.

184 **Procedure**

185 Participants were equipped with a 64 preamplified Ag–AgCl electrodes (International 10/10
186 system site, BrainAmp system). The ground electrode was placed at AFz, the reference
187 electrode at FCz, and the EEG signal sampling rate recording was 1000 Hz. Participants were
188 comfortably seated in a Faraday sound-proof booth in front of a computer screen (24”) with
189 a resolution of 1920 x 1080px and a refresh rate of 100Hz), at a distance of approximately 70
190 cm. A Gazepoint GP3 eye-tracker (sampling rate: 60 Hz; accuracy: 0.5-1° of visual angle) was
191 installed at the bottom of the screen on a tripod to record the participant’s gaze positions.
192 OpenSesame software (Mathôt et al., 2012) installed on a Dell laptop (Precision T1700)
193 launched the eye-tracker recording through the PyGaze package (Dalmaijer et al., 2014) and
194 the audio-visual stimulation. The videos were displayed on full screen resolution, and the
195 sound was delivered through a 2040 YAMAHA amplifier and two NS 1020 Studio YAMAHA
196 loudspeakers located on both sides of the screen. Before each video presentation, the
197 participant’s eyes were calibrated using the PyGaze’s standard 12-points calibration
198 procedure.

199 The experimenter asked participants to attentively follow the dialogues and informed them
200 that, after each dialogue, they should answer 12 questions on the dialogue content. These
201 questions allowed us to ascertain participants’ attention and assess the level of
202 comprehension. Each participant saw 2 dialogues in each of the three experimental
203 conditions (normal speech, moderately degraded speech, highly degraded speech). The level
204 of degradation of each dialogue and the order of the dialogues were counterbalanced across
205 participants (each dialogue was presented at a different degradation level - normal,
206 moderately degraded, highly degraded - to different participants).

207

208 **Stimuli, eye-tracking and EEG data synchronization**

209 A custom-made sync box based on an Arduino micro-controller ensured the synchronization
210 between the EEG data and the acoustic stimulation that was embedded in the video file. The
211 stereo sound goes from the stimulation PC to the sync box (audio cable). There, the stereo is
212 split and the first channel containing the speech signals of the dialogues goes directly to the
213 loudspeakers. The second channel signal goes through the micro-controller. This channel
214 contains an audio trigger indicating the beginning and the end of each dialogue. The Arduino
215 detects the audio trigger and sends an adapted signal to the EEG system. To ensure a precise
216 synchronization of the eye-tracking on the acoustic stimulation and the EEG data, we used
217 saccadic movements. More precisely, saccades can be easily detected in the eye-tracking
218 data, but they are also clearly visible in the EEG signal, especially using Independent
219 Component Analysis decomposition (Makeig et al., 1996). Thus, for each dialogue, we
220 detected gaze switch for every turn in both the eye-tracking and EEG data (see
221 supplementary material 1). Then, we computed for each subject and dialogue the median
222 delay between the two signals across all turns and used it to temporally realign the eye-
223 tracking to EEG (median delay across participants = 23ms; median sd across participants =
224 12ms). This procedure ensured a good time-alignment of the three types of data (video, eye-
225 tracking and EEG).

226 **Data Analysis**

227 Eye-tracking

228 In this study we used the gaze switch from one speaker to the other as a proxy of
229 anticipatory behaviour with respect to the upcoming turn onset (see Figure 1A left and B).
230 However, in contrast with previous studies (Casillas & Frank, 2017) that were mostly
231 interested in anticipatory gaze shift, we were also interested in somewhat late gaze shifts.

232 We assumed that adult participants need approximately 200ms to plan an eye movement
233 (Kamide et al., 2003). Thus, we considered a temporal window around the turn allowing to
234 keep both anticipatory and non-anticipatory gaze switch, resulting in a -1/+1s window
235 around the turn onset (Figure 1B). Note, nonetheless that, as expected, most shifts occurred
236 in the inter-turn gap, that is before the turn onset (Foulsham et al., 2010; Keitel et al. 2013;
237 Casillas and Frank 2017, see Figure 2B).

238 Moreover, we also applied three supplementary criteria to filter spurious gaze switches.
239 First, gaze before and after the switch should fall within an area of interest (AOIs), defined as
240 stationary rectangle surrounding each face (see Figure 1A left). Second, gaze switch should
241 be preceded by at least 100ms fixation on the current speaker. Third, it should be followed
242 by at least 150ms fixation to the next speaker. Concerning the possible back and forth gaze
243 behaviour preceding turn (4.5% in our data), we kept only the first gaze switch.

244 In short, we computed a gaze switch latency, that is relative to the upcoming turn onset
245 time. A positive indicates thus a gaze switch following the turn onset, while a negative value
246 indicates a gaze switch before the turn onset (Figure 1C left). Then, we used a median split
247 to class turns as early or late, separately for each subject and condition (Figure 1C right).

248 EEG

249 Signal processing was done using EEGLAB (Delorme & Makeig, 2004) and custom scripts
250 written in MATLAB. We high-pass filtered (0.5Hz) continuous data and rejected major
251 artifacts ($> 300 \mu\text{V}$). For every participant, we systematically used Independent Component
252 Analysis to remove eye blinks and saccadic movements and, when needed, muscular activity.
253 We then low-pass filtered (45Hz) and segmented continuous data into epochs of 900ms
254 starting at 100ms prior to turn onset. We zero-mean normalized epochs to the baseline ([–

255 100, 0]ms) and re-referenced to the algebraic average of all electrodes. Finally, we averaged
256 epochs according to the three conditions, also separating epochs according to the latency of
257 the gaze shift corresponding to each turn (early or late, see above).

258 **Statistical analysis**

259 We computed all statistical analysis using R (Team, 2021) and the lme4 package (Bates et al.,
260 2015). We evaluated participants' comprehension scores (1 point attributed to each good
261 answer; range 0 - 12) as a function of speech degradation by fitting linear models on the
262 mean of correct responses for each condition (2 dialogues by condition) and each subject.
263 Similarly, we modelled the mean of gaze switch latencies for each dialogue as a function of
264 speech degradation by fitting linear model on latency data. We then used a general linear
265 model (glm) in modelling the time spent gazing at the current speaker (ratio of the total
266 fixation time). All these models were tested against the null model before being
267 interpreted. We computed a linear mixed model with interaction to explain comprehension
268 score according to gaze switch latencies and speech degradation, with subject as random
269 effect (`comprehension ~ gaze switch latency * speech degradation + 1 | subject`). This model
270 was compared 1) to the null model, 2) to the model with only gaze switch latencies as
271 predictor and 3) to the additive model (gaze switch latencies and speech degradation as
272 independent predictors). Statistical significance of the fixed effects was assessed by model
273 comparison using the Akaike Information Criterion, thus arbitrating between complexity and
274 explanatory power of the models. Normality and homoscedasticity of the residuals of all the
275 models were systematically visually inspected. Reported p values are Satterthwaite
276 approximations obtained with the lmerTest package (Kuznetsova et al., 2017).

277 The statistical significance of the differences between conditions for the ERP data was
278 evaluated by a cluster-based random permutation approach for the full set of 64 electrodes
279 (2-tailed test with 500 permutations over the whole time range of the ERP epoch, i.e.
280 between -100 and 800ms). This statistical approach handles the multiple-comparisons
281 problem. More precisely, the approach controls for the Type-1 error rate in multiple testing
282 across channels and time points by identifying clusters of significant differences between
283 conditions in the time and space dimensions (Maris & Oostenveld, 2007). Finally, in order to
284 assess the relation between gaze switch and ERPs, we used simple linear models with the
285 amplitude difference between late and early trials in the N400 window explained as a
286 function of the interaction between gaze switch latencies and speech degradation (N400
287 effect \sim gaze switch latency * speech degradation). As for the other analyses, this model was
288 compared to the additive model.

289

290 Results

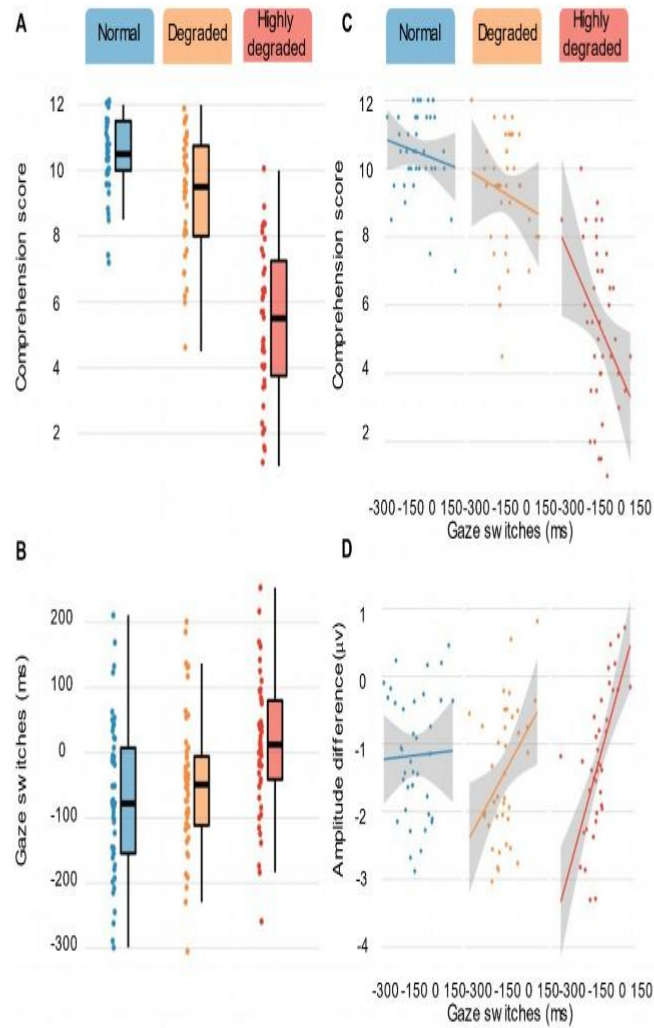
291 As expected, the comprehension score decreases as a function of increasing speech
292 degradation ($\beta = -2.551$, SE = 0.22, $t = -11.55$, $p < 0.001$, Figure 2A). Compared to the normal
293 condition, both the highly degraded and degraded speech conditions altered the
294 comprehension score ($\beta = -1.23$, SE = 0.42, $t = -2.929$ $p = 0.004$; $\beta = -5.102$, SE = 0.42, $t = -$
295 12.145, $p < 0.001$, respectively).

296 It is important to note that participants' score are well above zero and this is also the case in
297 the highly degraded condition (range: 1-10, median 5.5). Considering that the score is based
298 on response to open questions, it is extremely unlikely that a single correct answer is given

299 by chance. As such, these results show that participants of the current experiment can partly
300 understand the dialogues even in the most difficult condition of speech perception.

301 When turning to eye-movements, participants gaze data are available on average for 87% of
302 the total duration of the dialogues (range: [82-90]). The loss of data is possibly due to a gaze
303 off the screen and/or to a temporary loss of the eye from the tracker. From these available
304 data, it appears that participants gazed at the current speaker most of the time during video
305 playback (93%; range: [87-97]). Compared to the normal condition, time spent on current
306 speaker is greater in the degraded ($\beta = 0.580$, $SE = 0.073$, $t = 7.881$, $p < 0.001$) and highly
307 degraded conditions ($\beta = 0.616$, $SE = 0.074$, $t = 8.317$, $p < 0.001$). Importantly, not only
308 participants gazed most of the time at the current speaker, but when considering gaze
309 switch towards the current speaker, these took place most often in a -1/+1sec window
310 around the turn onset (mean 80 %, range: [0.56-0.96]), the rest being gaze switches far away
311 from the turn or missing data.

Figure 2



312

313 Figure 2. Behavioural results and correlations. A. Effect of speech degradation level on comprehension. Dots

314 represent the average comprehension score for each participant in each condition. B. Effect of speech

315 degradation level on gaze switch latency. Latency at zero milliseconds corresponds to the onset of the turn.

316 Dots represent the average latency for each participant in each condition. C. Scatter plots and linear regression

317 between comprehension scores and gaze switch latency in the three different conditions. D. Scatter plots and

318 linear regression between N400 effect size (late minus early, in the 300-550ms latency window) and gaze

319 switch latency in the three different conditions.

320 Normalizing by time unit this gives a number of gaze switch per second of 0.47 during the

321 turn window and 0.08 during the rest of the dialogue (that is switches from one AOI to the

322 other that were performed outside the -1/+1s window around the turn, see supplementary
323 material 2). Overall, these results clearly show that gaze and gaze switches are not randomly
324 distributed across the dialogues. On the contrary, gaze behaviour to current speakers
325 demonstrates that participants are tracking turns during the videos, as previously reported
326 (Casillas & Frank, 2017). When moving to gaze switch latencies, one can see that these are
327 influenced by speech degradation ($\beta = 43.382$, SE = 9.52, $t = 4.553$, $p < 0.001$, see Figure 2B).
328 This is due to longer latencies to turns with highly degraded speech compared to normal and
329 degraded speech (always $p < 0.001$) while there are no latency differences between
330 degraded and normal conditions ($p > 0.1$). Moreover, latencies globally move from negative
331 values in the normal condition to positive values in the highly degraded condition. Because
332 latencies are estimated with respect to turn onset, this means that while in the normal
333 condition participants realize the gaze switch before the turn, switches mostly take place
334 after the turn onset in the highly degraded condition.

335 When looking at the relation between comprehension scores and gaze latency, this changes
336 as a function of speech degradation ($\beta = - 5.740$, SE = 0.001, $t = -3.936$, $p < 0.001$). More
337 precisely, in the highly degraded condition shorter gaze switch latencies to turn onsets are
338 associated to good comprehension scores ($\beta = - 0.008$, SE = 0.003, $t = -2.989$, $p < 0.01$). This
339 effect was not significant in the moderately degraded nor in normal conditions ($p > 0.5$,
340 Figure 2C). This model with gaze switch latencies and speech degradation as interaction
341 factors was the best compared to the additive model (AIC = 1038.5 and 1043.6 respectively ;
342 $p < 0.01$ and $p < 0.001$).

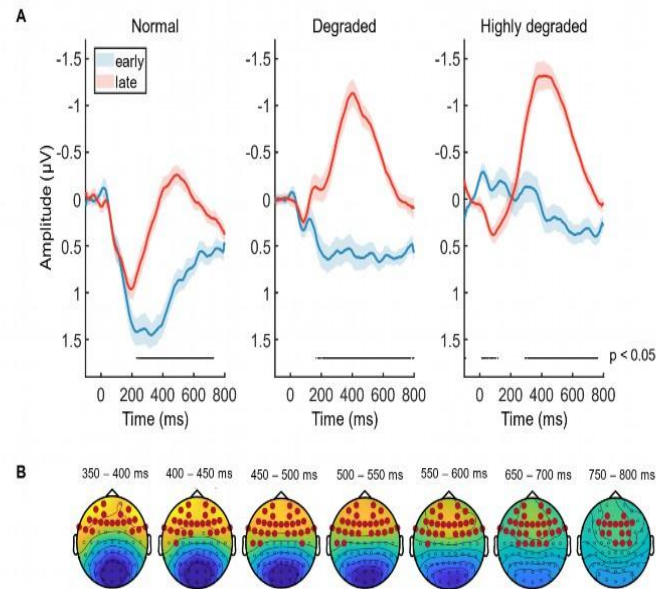
343 The classification of turns on the basis of the latency of gaze switches (**late vs early**) shows a
344 clear negative component for turns with late switches evolving between 350 and 700ms

345 post-stimulus onset over a fronto-central region (Figure 3B). This effect is visible in the three
346 different levels of speech degradation ($p < 0.05$, FDR corrected). However, this effect seems
347 to differ across the three levels of speech degradation (Figure 3A) insofar as the clusters
348 start at different latencies. Because it is not appropriate to make an inferential claim on the
349 time extension of the cluster (Sassenhagen et al., 2019), we run a further analysis using a
350 jackknife approach in five subsequent 50ms latency windows from 150 to 400ms. This
351 approach is considered appropriate to make inferences on the latency of an ERP effect
352 (Miller et al., 1998). Results show that differences between early and late turns are
353 significant starting 200ms post turn onset in the normal condition, 150ms in the moderately
354 degraded condition and 300ms in the highly degraded condition ($p < 0.05$, FDR corrected).

355 Finally, when looking at the relation between the ERP effect (late vs early gaze switches) in
356 the 300-550ms window and the global gaze switch latency of participants, we find a
357 significant interaction between gaze switch latencies and speech degradation levels ($F =$
358 7.135 , $p = 0.001$). More precisely, one can notice, that, in the highly degraded condition,
359 participants with overall shorter gaze switch latencies to turn onsets show a larger effect ($\beta =$
360 0.007 , $SE = 0.001$, $t = 3.753$, $p < 0.001$). A similar but not significant trend is also visible in the
361 moderately degraded ($\beta = 0.003$, $SE = 0.001$, $t = 1.912$, $p = 0.058$) but not in the normal

362 conditions ($\beta = 0.000$, $SE = 0.001$, $t = 0.204$, $p = 0.838$, Figure 2D).

Figure 3



363

364 Figure 3. A. event-related potentials (ERPs) in a fronto-central region of interest time-locked to the turn onset
365 for early and late gaze switch latencies. Shaded areas indicate the standard error of the mean. The black line
366 below the ERPs indicates the FDR corrected significant difference between early and late conditions. B.

367 Cluster-based statistical analyses on all electrodes showing the main effect of gaze behaviour (early vs late).

368 The topography illustrates the **difference** between late and early turns across all levels of degradation. The red
369 dots represent electrodes with significant differences (cluster corrected).

370 Discussion

371 In the present experiment, participants watched a series of videos showing two interlocutors
372 having a conversation. We parametrically degraded speech and measured eye-movements,
373 EEG and dialogue comprehension to gather a deeper understanding of the mechanisms
374 underlying speech comprehension under challenging conditions. We build on the fact that

375 participants switch gaze at the current speaker and use this measure as a proxy of prediction
376 to class dialogue turns as more or less well predicted and study ERPs accordingly. Results
377 show that 1) Participants switch gaze towards the current speaker in a limited temporal
378 window around the turn. 2) Speech degradation reduces the anticipatory gaze behaviour. 3)
379 Globally, participants with a low comprehension score tend to have a later gaze behaviour
380 when speech is strongly degraded. 4) ERPs to turn onsets vary as a function of the latency of
381 the gaze switch. 5) Finally, participants with overall shorter switch gaze latencies show a
382 better comprehension score and a stronger anticipatory effect in their neural responses; this
383 relation between behavioural and neural variables is significant only in the most challenging
384 (degraded) condition. We discuss these findings with respect to the relation between
385 predictions, neural predictions errors and speech comprehension under challenging
386 conditions. Of course, these findings are limited by the constraints inherent to the present
387 experiment, wherein predictions are possible purposely on the basis of auditory cues only
388 because we controlled all extralinguistic visual cues (e.g. lip preparatory movement) that
389 undoubtedly play an important role in conversation.

390 Our study replicates previous findings (Casillas & Frank, 2017; Foulsham et al., 2010; Keitel et
391 al., 2013), showing that gaze switch takes place in a precise temporal window centered
392 before turn onset. Considering the short period between turns and the time needed to
393 prepare and realize a saccade, gaze switch, in this context, can be interpreted as anticipatory
394 behaviour (Keitel & Daum, 2015). The new result, in this respect, is that gaze switch
395 behaviour is affected by the more or less challenging speech comprehension, here obtained
396 by spectrally degrading speech signal. The reduction of anticipatory gaze behaviour in
397 presence of stronger speech degradation seems to indicate that increasing the cost of
398 speech processing has a detrimental effect on the prediction of the upcoming turn. This is in

399 line with results on hearing-impaired individuals showing a delay (greater effort) in
400 processing sentences with more or less contextual cues, compared to normal-hearing (Winn,
401 2016).

402 Importantly, our results show a relation between comprehension score and turn anticipatory
403 behaviour, under challenging conditions. This result is not trivial. Indeed, the comprehension
404 score reflects the global understanding of the whole dialogues, because it corresponds to
405 questions that were asked at the end of each dialogue. By contrast, gaze switch and EEG
406 dynamics reflect anticipatory behaviour at precise temporal windows surrounding
407 conversational turns. This means, that, under challenging conditions, participants that are
408 able to understand can take advantage of an anticipatory gaze behaviour. Alternatively,
409 participants with an anticipatory gaze behaviour are better able to understand. While the
410 present design does not allow for a causal interpretation between gaze behaviour and global
411 understanding of the dialogues, we will see that ERP results play here a very important role.
412 However, before discussing this point one has to interpret the ERP components, in particular
413 the negative component peaking around 400ms.

414 First, one may raise the possibility that residual gaze-related artefact may still be present in
415 the EEG, even following ICA procedures (see methods). However, 1) the systematic
416 difference in latency between late and early switches was on average 480ms, while we do
417 not observe such a delay in ERPs to early and late turns; 2) while highly degraded speech
418 induces overall later gaze switches, the N400 peak in this condition has the same latency as
419 in the other conditions (in Figure 3A the N400 peak is always 400ms). Thus, overall, one can
420 consider that differences in ERPs are due to cognitive processes and not to residual
421 physiological artefacts due to eye movements.

422 The first and most likely interpretation of the larger negativity to both degraded turns and
423 late turns is in terms of an N400 like component. Indeed, the amplitude of the N400 is
424 strongly affected by expectations: the more a target word is unexpected within a sentence
425 context, the larger the N400 amplitude (Kutas & Federmeier, 2011; Kutas & Hillyard, 1984).
426 While the N400 topography we report is more anterior compared to the classic centro-
427 parietal distribution, this may be due to the audiovisual modality (Kelly et al., 2004) or to the
428 presence of complex scenes (Kutas & Federmeier, 2011) inducing a topography more frontal
429 than for written words. Importantly, the N400 has been proposed to be a proxy of prediction
430 errors (Bornkessel-Schlesewsky & Schlewsky, 2019; Rabovsky & McRae, 2014), that play a
431 key role within the predictive coding framework (Friston, 2010; Schultz & Dickinson, 2000).

432 As stated above, in order to assess the relevance of predictive coding theories with respect
433 to speech comprehension, it is necessary to have access to both prediction and prediction
434 error indicators. Our results, as well as previous studies, seem quite clear in showing that
435 gaze switch behaviour can be considered as a proxy of predictions. Previous research using
436 an electrophysiological marker of prediction (the semantic prediction potential, SPP) showed
437 that smaller SPP amplitude (weak predictions) result in a large N400 (Grisoni et al., 2021).
438 Similarly, our results show that turns preceded by a late gaze switch, indicating poor
439 predictions, give rise to a larger N400 like complex compared to turns preceded by an early
440 gaze switch. An interesting advantage of the current design is that the target words (here
441 turn onsets) do not need to differ in content or in context in order to engender a N400. This
442 is different for instance, from previous studies manipulating the semantic and temporal turn
443 relation to induce an N400 effect (Bögels et al., 2015). In other words, in the current study,
444 the word and the context eliciting or not the N400 are strictly identical and we take
445 advantage of the natural variability in the accuracy of participants' predictions across turns.

446 The interpretation in terms of N400 also fits quite well with the literature on weaker
447 expectancies under degraded speech. Previous work showed that adverse listening
448 conditions narrow the expectancies about the upcoming speech. This is visible in a reduced
449 N400 effect in response to incongruent or less likely words under acoustic degradation
450 (Aydelott et al., 2006; Obleser & Kotz, 2011; Strauß et al., 2013). The present findings show a
451 somewhat similar result, with an N400 effect that is significant in a later latency window in
452 the most challenging condition (strong speech degradation) compared to the two other
453 conditions. While the typical N400 effect concerns the amplitude of the negative wave,
454 several works reported later N400 latencies in context presenting more difficult semantic
455 access (Deacon et al., 1995; Moreno & Kutas, 2005). Interestingly, the temporal window
456 analysis shows that traces to early and late turns diverge first in the degraded condition,
457 then in the normal and last in the highly degraded conditions. It thus seems as if the
458 advantage of an early gaze switch was integrated faster in moderately challenging
459 conditions. There, the benefit of an anticipatory gaze behaviour and temporally precise
460 (local) predictions may be maximal compared to the two other conditions wherein
461 uncertainty may either be too low (normal speech) or too high (highly degraded speech).

462 However, while the N400 latency is earliest in the degraded condition (Figure 3A), the N400
463 amplitude best correlates with turn anticipatory behaviour in the highly degraded condition
464 (Figure 2D). In considering this inconsistency one should keep in mind that 1) the N400
465 effect, in terms of amplitude, is also significant in the highly degraded condition; 2) while the
466 correlation between N400 amplitude and average gaze behaviour does not reach the
467 significance threshold ($p = .06$), the trend of the correlation is similar across the two
468 degraded conditions.

469 Importantly, Figure 2C and 2D clearly show that there is a similar relation between gaze
470 behaviour and the semantic access of dialogues. Differently from global comprehension
471 score, the N400 amplitude does not reflect a global understanding of the conversation, but it
472 is a rather local measure, as it is the case with gaze switch behaviour. Moreover, the two
473 measures are serially ordered in time, with gaze switch taking place earlier ~400ms before
474 the N400 peak. Thus, one can hypothesize that participants with an overall early gaze switch,
475 by having a better prediction of the turn, have an easier lexical-semantic integration of the
476 word starting the turn in the conversational context. This relation between gaze and both
477 local (N400 effect) and global (comprehension scores) understanding is only shown under
478 challenging conditions, wherein indeed participants can benefit of a predictive behaviour to
479 improve their understanding of the dialogues.

480 It seems appropriate here to evoke an alternative (although not necessarily the most likely)
481 interpretation of the negative component in terms of a phonological mismatch negativity
482 (pMMN). Several studies have addressed the timing of audio-visual integration. For instance,
483 in McGurk illusion, the temporal window allowing modality fusion and allusion ranges
484 between 30ms and 170ms of asynchrony (van Wassenhove et al., 2007). When looking at
485 the electrophysiological response to the incongruent audio-visual stimulation, several
486 authors report a pMMN (Colin et al., 2002; Eskelund et al., 2015; Stekelenburg & Vroomen,
487 2012). The latency of this response is later than the classic MMN and is described
488 approximately 500ms after the voice onset (Proverbio et al., 2018). In our study, the
489 classification of turns as being accompanied by late or early gaze switch implies that the
490 audio-visual relation of the stimuli differs in the two classes. For early gaze switch, the gaze
491 is well anticipated and thus the audio-visual information is perceived simultaneously. By
492 contrast, in turns with a late gaze switch, often occurring after the voice onset, the

493 audiovisual integration has a higher level of **uncertainty**. In other words, if a gaze switch
494 takes place later than a turn onset, there may be an audiovisual mismatch because the
495 participant is looking at the previous speaker while listening to the upcoming speaker's
496 voice. In this context, looking at the closed lips of the previous speaker and hearing the word
497 pronounced by the following speaker, may engender a phonological audiovisual MMN.

498 We would like to end the discussion with a consideration on the implicit and explicit role of
499 predictions. It is known that the influences of the visual system on auditory perception can
500 be so strong as to override under certain conditions the original input of the auditory system
501 (McGurk & Macdonald, 1976). More commonly, viewing the lips provides relevant
502 complementary information and can augment and improve auditory capabilities (Calvert et
503 al., 1997; Drijvers & Özyürek, 2017; Grant & Seitz, 2000; Sumbly & Pollack, 1954). In this
504 context, it is interesting to note that, compared to the normal condition, the moderately
505 degraded condition yields a poorer comprehension but similar gaze switch latencies and an
506 earlier N400 effect. These preserved latencies, in a context of poorer comprehension that
507 should rather induce poorer predictions, may be mediated by an active compensatory
508 strategy, explicitly making greater use of visual cues to improve predictive processes
509 (Sohoglu & Davis, 2016). Such a compensatory strategy may not hold when speech is highly
510 degraded, yielding to slower gaze switches due to a poor understanding of the semantic and
511 syntactic context. The respective role of implicit and explicit predictions and their link to
512 conversation strategies (Hadley et al., 2021) will require further work addressing this specific
513 question. **Another interesting aspect that will require further work is the inter-relation**
514 **between local predictions (gaze), local semantic processing (N400) and global**
515 **comprehension (here assessed via specific questions on the dialogues). While on one side**
516 **gaze switches temporally precede auditory and semantic processing of the upcoming turn,**

517 this anticipatory behaviour can only build on the global comprehension of the dialogue, that,
518 in turn, depends on the integration of local semantic processing.

519 To conclude, this study confirms that gaze switch can be used as a proxy of predictions in a
520 conversational context. It shows that these predictions are related to the lexico-semantic
521 processing of the turn start, as estimated by a neural marker of prediction error. It also
522 shows that predictions are less accurate in more challenging listening conditions, but that
523 they are also most useful in that specific context to make sense of the upcoming turn and,
524 more generally, are a good indicator of global dialogue comprehension.

525 **Acknowledgements**

526 We would like to thank Laura Leone, Romane Pradels and Benjamin Morillon for their
527 participation in the design of the dialogues and the production of videos.

528 **Funding sources:** Work supported by APA foundation (RD-2016-9), ANR-16-CONV-0002
529 (ILCB) and the Excellence Initiative of Aix-Marseille University (A*MIDEX).

530

531 **References**

532 Aydelott, J., Dick, F., & Mills, D. L. (2006). Effects of acoustic distortion and semantic context
533 on event-related potentials to spoken words. *Psychophysiology*, 43(5), 454–464.

534 <https://doi.org/10.1111/j.1469-8986.2006.00448.x>

535 Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting Linear Mixed-Effects Models
536 Using {lme4}. *Journal of Statistical Software*, 67(1), 1–48.

537 <https://doi.org/10.18637/jss.v067.i01>

- 538 Beňuš, Š., Gravano, A., & Hirschberg, J. (2011). Pragmatic aspects of temporal
539 accommodation in turn-taking. *Journal of Pragmatics*, *43*(12), 3001–3027.
540 <https://doi.org/10.1016/j.pragma.2011.05.011>
- 541 Bögels, S., Kendrick, K. H., & Levinson, S. C. (2015). Never say no . . . How the brain interprets
542 the pregnant pause in conversation. *PLoS ONE*, *10*(12).
543 <https://doi.org/10.1371/journal.pone.0145474>
- 544 Bornkessel-Schlesewsky, I., & Schlesewsky, M. (2019). Toward a neurobiologically plausible
545 model of language-related, negative event-related potentials. *Frontiers in Psychology*,
546 *10*(FEB), 298. <https://doi.org/10.3389/fpsyg.2019.00298>
- 547 Calvert, G. A., Bullmore, E. T., Brammer, M. J., Campbell, R., Williams, S. C. R., McGuire, P. K.,
548 Woodruff, P. W. R., Iversen, S. D., & David, A. S. (1997). Activation of auditory cortex
549 during silent lipreading. *Science*, *276*(5312), 593–596.
550 <https://doi.org/10.1126/science.276.5312.593>
- 551 Casillas, M., & Frank, M. C. (2017). The development of children’s ability to track and predict
552 turn structure in conversation. *Journal of Memory and Language*, *92*, 234–253.
553 <https://doi.org/10.1016/j.jml.2016.06.013>
- 554 Clark, A. (2013). Whatever next? Predictive brains, situated agents, and the future of
555 cognitive science. *Behavioral and Brain Sciences*, *36*(3), 181–204.
556 <https://doi.org/10.1017/S0140525X12000477>
- 557 Colin, C., Radeau, M., Soquet, A., Demolin, D., Colin, F., & Deltenre, P. (2002). Mismatch
558 negativity evoked by the McGurk-MacDonald effect: A phonetic representation within
559 short-term memory. *Clinical Neurophysiology*, *113*(4), 495–506.

560 [https://doi.org/10.1016/S1388-2457\(02\)00024-X](https://doi.org/10.1016/S1388-2457(02)00024-X)

561 Dalmaijer, E. S., Mathôt, S., & Van der Stigchel, S. (2014). PyGaze: an open-source, cross-
562 platform toolbox for minimal-effort programming of eyetracking experiments. *Behavior*
563 *Research Methods*, 46(4), 913–921. <https://doi.org/10.3758/s13428-013-0422-2>

564 De Ruiter, J., Mitterer, H., & Enfield, N. J. (2006). Projecting the end of a speaker’s turn: a
565 cognitive cornerstone of conversation. *Language*, 82, 515–535.
566 <http://dx.doi.org/10.1353/lan.2006.0130>

567 Deacon, D., Mehta, A., Tinsley, C., & Nousak, J. M. (1995). Variation in the latencies and
568 amplitudes of N400 and NA as a function of semantic priming. *Psychophysiology*, 32(6),
569 560–570.
570 [http://search.ebscohost.com/login.aspx?direct=true&db=s3h&AN=11064097&lang=fr&](http://search.ebscohost.com/login.aspx?direct=true&db=s3h&AN=11064097&lang=fr&site=ehost-live)
571 [site=ehost-live](http://search.ebscohost.com/login.aspx?direct=true&db=s3h&AN=11064097&lang=fr&site=ehost-live)

572 Delorme, A., & Makeig, S. (2004). EEGLAB: an open source toolbox for analysis of single-trial
573 EEG dynamics. *Journal of Neuroscience Methods*, 13, 9–21.
574 <https://doi.org/http://dx.doi.org/10.1016/j.jneumeth.2003.10.009>

575 Drijvers, L., & Özyürek, A. (2017). Visual context enhanced: The joint contribution of iconic
576 gestures and visible speech to degraded speech comprehension. *Journal of Speech,*
577 *Language, and Hearing Research*, 60(1), 212–222. [https://doi.org/10.1044/2016_JSLHR-](https://doi.org/10.1044/2016_JSLHR-578)
578 [H-16-0101](https://doi.org/10.1044/2016_JSLHR-H-16-0101)

579 Eskelund, K., MacDonald, E. N., & Andersen, T. S. (2015). Face configuration affects speech
580 perception: Evidence from a McGurk mismatch negativity study. *Neuropsychologia*, 66,
581 48–54. <https://doi.org/10.1016/j.neuropsychologia.2014.10.021>

582 Foulsham, T., Cheng, J. T., Tracy, J. L., Henrich, J., & Kingstone, A. (2010). Gaze allocation in a
583 dynamic situation: Effects of social status and speaking. *Cognition*, 117(3), 319–331.
584 <https://doi.org/10.1016/j.cognition.2010.09.003>

585 Friston, K. (2005). A theory of cortical responses. *Philosophical Transactions of the Royal*
586 *Society B: Biological Sciences*, 360(1456), 815–836.
587 <https://doi.org/10.1098/rstb.2005.1622>

588 Friston, K. (2010). The free-energy principle: A unified brain theory? *Nature Reviews*
589 *Neuroscience*, 11(2), 127–138. <https://doi.org/10.1038/nrn2787>

590 Grant, K. W., & Seitz, P.-F. (2000). The use of visible speech cues for improving auditory
591 detection of spoken sentences. *The Journal of the Acoustical Society of America*, 108(3),
592 1197. <https://doi.org/10.1121/1.1288668>

593 Grisoni, L., Tomasello, R., & Pulvermüller, F. (2021). Correlated Brain Indexes of Semantic
594 Prediction and Prediction Error: Brain Localization and Category Specificity. *Cerebral*
595 *Cortex*, 31(3), 1553–1568. <https://doi.org/10.1093/cercor/bhaa308>

596 Hadley, L. V., Whitmer, W. M., Brimijoin, W. O., & Naylor, G. (2021). Conversation in small
597 groups: Speaking and listening strategies depend on the complexities of the
598 environment and group. *Psychonomic Bulletin & Review*, 28(2), 632-640.

599 Hirvenkari, L., Ruusuvuori, J., Saarinen, V.-M., Kivioja, M., Peräkylä, A., & Hari, R. (2013).
600 Influence of Turn-Taking in a Two-Person Conversation on the Gaze of a Viewer. *PLoS*
601 *ONE*, 8(8), e71569. <https://doi.org/10.1371/journal.pone.0071569>

602 Kamide, Y., Altmann, G. T. M., & Haywood, S. L. (2003). The time-course of prediction in
603 incremental sentence processing: Evidence from anticipatory eye movements. *Journal*

604 *of Memory and Language*, 49(1), 133–156. <https://doi.org/10.1016/S0749->
605 596X(03)00023-8

606 Keitel, A., & Daum, M. M. (2015). The use of intonation for turn anticipation in observed
607 conversations without visual signals as source of information. *Frontiers in Psychology*,
608 6(February), 108. <https://doi.org/10.3389/fpsyg.2015.00108>

609 Keitel, A., Prinz, W., Friederici, A. D., Hofsten, C. von, & Daum, M. M. (2013). Perception of
610 conversations: The importance of semantics and intonation in children’s development.
611 *Journal of Experimental Child Psychology*, 116(2), 264–277.
612 <https://doi.org/10.1016/j.jecp.2013.06.005>

613 Kutas, M., & Federmeier, K. D. (2011). Thirty years and counting: Finding meaning in the
614 N400 component of the event-related brain potential (ERP). *Annual Review of*
615 *Psychology*, 62, 621–647. <https://doi.org/10.1146/annurev.psych.093008.131123>

616 Kutas, M., & Hillyard, S. A. (1984). Brain potentials during reading reflect word expectancy
617 and semantic association. *Nature*, 307(5947), 161–163.

618 Kuznetsova, A., Brockhoff, P. B., & Christensen, R. H. B. (2017). lmerTest Package: Tests in
619 Linear Mixed Effects Models. *Journal of Statistical Software*, 82(13), 1–26.
620 <https://doi.org/10.18637/jss.v082.i13>

621 Levinson, S. C. (2016). Turn-taking in Human Communication - Origins and Implications for
622 Language Processing. *Trends in Cognitive Sciences*, 20(1), 6–14.
623 <https://doi.org/10.1016/j.tics.2015.10.010>

624 Makeig, S., Bell, A. J., Jung, T.-P., & Sejnowski, T. J. (1996). Independent component analysis
625 of electroencephalographic data. *Advances in Neural Information Processing Systems*,

626 145–151.

627 Maris, E., & Oostenveld, R. (2007). Nonparametric statistical testing of EEG- and MEG-data.
628 *Journal of Neuroscience Methods*, 164(1), 177–190.
629 <https://doi.org/10.1016/j.jneumeth.2007.03.024>

630 Mathôt, S., Schreij, D., & Theeuwes, J. (2012). OpenSesame: An open-source, graphical
631 experiment builder for the social sciences. *Behavior Research Methods*, 44(2), 314–324.
632 <https://doi.org/10.3758/s13428-011-0168-7>

633 Mattys, S. L., Davis, M. H., Bradlow, A. R., & Scott, S. K. (2012). Speech recognition in adverse
634 conditions: A review. *Language and Cognitive Processes*, 27(7–8), 953–978.
635 <https://doi.org/10.1080/01690965.2012.705006>

636 Mcgurk, H., & Macdonald, J. (1976). Hearing lips and seeing voices. *Nature*, 264(5588), 746–
637 748. <https://doi.org/10.1038/264746a0>

638 Miller, J., Patterson, T. U. I., & Ulrich, R. (1998). Jackknife-based method for measuring LRP
639 onset latency differences. *Psychophysiology*, 35(1), 99-115.

640 Molinaro, N., Monsalve, I. F., & Lizarazu, M. (2016). Is there a common oscillatory brain
641 mechanism for producing and predicting language? *Language, Cognition and*
642 *Neuroscience*, 31(1), 145–158. <https://doi.org/10.1080/23273798.2015.1077978>

643 Moreno, E. M., & Kutas, M. (2005). Processing semantic anomalies in two languages: An
644 electrophysiological exploration in both languages of Spanish-English bilinguals.
645 *Cognitive Brain Research*, 22(2), 205–220.
646 <https://doi.org/10.1016/j.cogbrainres.2004.08.010>

647 Obleser, J., & Kotz, S. A. (2011). Multiple brain signatures of integration in the
648 comprehension of degraded speech. *NeuroImage*, *55*(2), 713–723.
649 <https://doi.org/10.1016/j.neuroimage.2010.12.020>

650 Peelle, J. E. (2018). Listening effort: How the cognitive consequences of acoustic challenge
651 are reflected in brain and behavior. *Ear and Hearing*, *39*(2), 204–214.
652 <https://doi.org/10.1097/AUD.0000000000000494>

653 Pickering, M. J., & Gambi, C. (2018). Predicting while comprehending language: A theory and
654 review. *Psychological Bulletin*, *144*(10), 1002–1044.
655 <https://doi.org/10.1037/bul0000158>

656 Proverbio, A. M., Raso, G., & Zani, A. (2018). Electrophysiological Indexes of Incongruent
657 Audiovisual Phonemic Processing: Unraveling the McGurk Effect. *Neuroscience*, *385*,
658 215–226. <https://doi.org/10.1016/j.neuroscience.2018.06.021>

659 Rabovsky, M., & McRae, K. (2014). Simulating the N400 ERP component as semantic network
660 error: Insights from a feature-based connectionist attractor model of word meaning.
661 *Cognition*, *132*(1), 68–89. <https://doi.org/10.1016/j.cognition.2014.03.010>

662 Rayner, K. (1978). Eye movements in reading and information processing. *Psychological*
663 *Bulletin*, *85*(3), 618–660. <https://doi.org/10.1037/0033-2909.85.3.618>

664 Roberts, S. G., Torreira, F., & Levinson, S. C. (2015). The effects of processing and sequence
665 organization on the timing of turn taking: a corpus study. *Frontiers in Psychology*, *6*,
666 509. <https://doi.org/10.3389/fpsyg.2015.00509>

667 <https://doi.org/10.1093/cercor/bhl024>

668 Sassenhagen, J., & Draschkow, D. (2019). Cluster-based permutation tests of MEG/EEG data
669 do not establish significance of effect latency or location. *Psychophysiology*, 56(6),
670 e13335.

671 Schultz, W., & Dickinson, A. (2000). Neuronal coding of prediction errors. *Annual Review of*
672 *Neuroscience*, 23, 473–500. <https://doi.org/10.1146/annurev.neuro.23.1.473>

673 Selting, M. (1996). On the interplay of syntax and prosody in the constitution of turn-
674 constructional units and turns in conversation. *Pragmatics. Quarterly Publication of the*
675 *International Pragmatics Association (IPrA)*, 6(3), 371–388.
676 <https://doi.org/10.1075/prag.6.3.06sel>

677 Shannon, R. V, Zeng, F. G., Kamath, V., Wygonski, J., & Ekelid, M. (1995). Speech recognition
678 with primarily temporal cues. *Science*, 270(5234), 303–304.
679 <https://doi.org/10.1126/science.270.5234.303>

680 Sohoglu, E., & Davis, M. H. (2016). Perceptual learning of degraded speech by minimizing
681 prediction error. *Proceedings of the National Academy of Sciences of the United States*
682 *of America*, 113(12), E1747–E1756. <https://doi.org/10.1073/pnas.1523266113>

683 Šoškić, A., Jovanović, V., Styles, S. J., Kappenman, E. S., & Ković, V. (2021). How to do better
684 N400 studies: reproducibility, consistency and adherence to research standards in the
685 existing literature. *Neuropsychology Review*, 1-24.

686 Staub, A. (2015). The Effect of Lexical Predictability on Eye Movements in Reading: Critical
687 Review and Theoretical Interpretation. *Language and Linguistics Compass*, 9(8), 311–
688 327. <https://doi.org/10.1111/lnc3.12151>

689 Stekelenburg, J. J., & Vroomen, J. (2012). Electrophysiological correlates of predictive coding

690 of auditory location in the perception of natural audiovisual events. *Frontiers in*
691 *Integrative Neuroscience*, 6(MAY 2012), 1–7. <https://doi.org/10.3389/fnint.2012.00026>

692 Stivers, T., Enfield, N. J., Brown, P., Englert, C., Hayashi, M., Heinemann, T., Hoymann, G.,
693 Rossano, F., de Ruiter, J. P., Yoon, K.-E., & Levinson, S. C. (2009). Universals and cultural
694 variation in turn-taking in conversation. *Proceedings of the National Academy of*
695 *Sciences of the United States of America*, 106(26), 10587–10592.
696 <https://doi.org/10.1073/pnas.0903616106>

697 Strauß, A., Kotz, S. A., & Obleser, J. (2013). Narrowed expectancies under degraded speech:
698 Revisiting the N400. *Journal of Cognitive Neuroscience*, 25(8), 1383–1395.
699 https://doi.org/10.1162/jocn_a_00389

700 Sumbly, W. H., & Pollack, I. (1954). Visual Contribution to Speech Intelligibility in Noise.
701 *Journal of the Acoustical Society of America*, 26(2), 212–215.
702 <https://doi.org/10.1121/1.1907309>

703 Team, R. C. (2021). *R: A language and environment for statistical computing*. Vienna: R
704 *Project, 2017*.

705 Tyler, L. K., & Wessels, J. (1983). Quantifying contextual contributions to word-recognition
706 processes. *Perception & Psychophysics*, 34(5), 409-420

707 van Wassenhove, V., Grant, K. W., & Poeppel, D. (2007). Temporal window of integration in
708 auditory-visual speech perception. *Neuropsychologia*, 45(3), 598–607.
709 <https://doi.org/10.1016/j.neuropsychologia.2006.01.001>

710 Winn, M. (2016). Rapid Release From Listening Effort Resulting From Semantic Context, and
711 Effects of Spectral Degradation and Cochlear Implants. *Trends in Hearing*, 20, 1–17.

713 **Supplementary material**

Dialogue's number	Dialogue's length (seconds)	Number of turns	Number of questions/response pairs
1	269	60	40
2	247	46	26
3	185	62	36
4	258	60	38
5	253	66	40
6	248	62	36

714

715 Table 1. Dialogues's details.

716

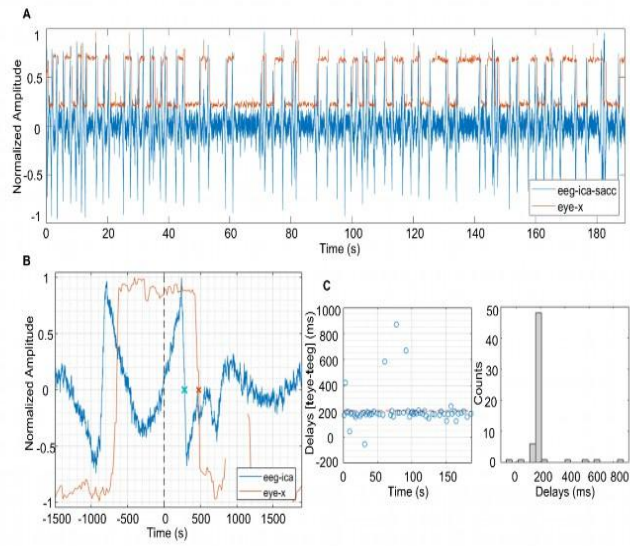
<p>Est-ce que Damien veut attraper une bête avec sa cage ?</p> <p><i>Does Damien want to catch an animal with his cage?</i></p>
<p>Cette cage est faite pour qui ?</p> <p><i>Who is this cage for?</i></p>
<p>Comment Damien arrive à rentrer dans sa cage ?</p> <p><i>How does Damien get into his cage?</i></p>
<p>Dans quoi peut rentrer le génie d'Aladin ?</p> <p><i>What can Aladdin's genie fit into?</i></p>

<p>Pourquoi Damien veut se cacher dans une cage ?</p> <p><i>Why does Damien want to hide in a cage?</i></p>
<p>Comment se déplace l'étrange fée ?</p> <p><i>How does the strange fairy move?</i></p>
<p>Qui porte un grand chapeau ?</p> <p><i>Who is wearing a big hat?</i></p>
<p>Pourquoi la sorcière veut attraper Damien ?</p> <p><i>Why does the witch want to catch Damien?</i></p>
<p>Camille va chercher qui pour aider Damien à se débarrasser de la méchante sorcière ?</p> <p><i>Who will Camille look for to help Damien get rid of the wicked witch?</i></p>
<p>Dans cette histoire, où habite Harry Potter ?</p> <p><i>In this story, where does Harry Potter live?</i></p>
<p>Pourquoi Camille pense qu'une bête s'est échappée ?</p> <p><i>Why does Camille think an animal has escaped?</i></p>
<p>Est-ce que Harry Potter aime les vilaines sorcières ?</p> <p><i>Does Harry Potter like bad witches?</i></p>

717

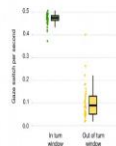
718 Table 2. Exemple of questions for one dialogue.

719



720

721 Supplementary material 1. Example of eye-tracking and EEG synchronization for one dialogue. A. Overlapping
 722 of ICA-EEG data and Eye-tracking data. B. Zoom in for one trial (one turn); latency at zero milliseconds
 723 corresponds to the onset of this turn. C. Dashed red line represents the mean of delays between Eye-tracking
 724 and EEG data for the same subject in the same dialogue as in A.



Supplementary material 2. Number of gaze switch per second in and out of the turn window.