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

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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.

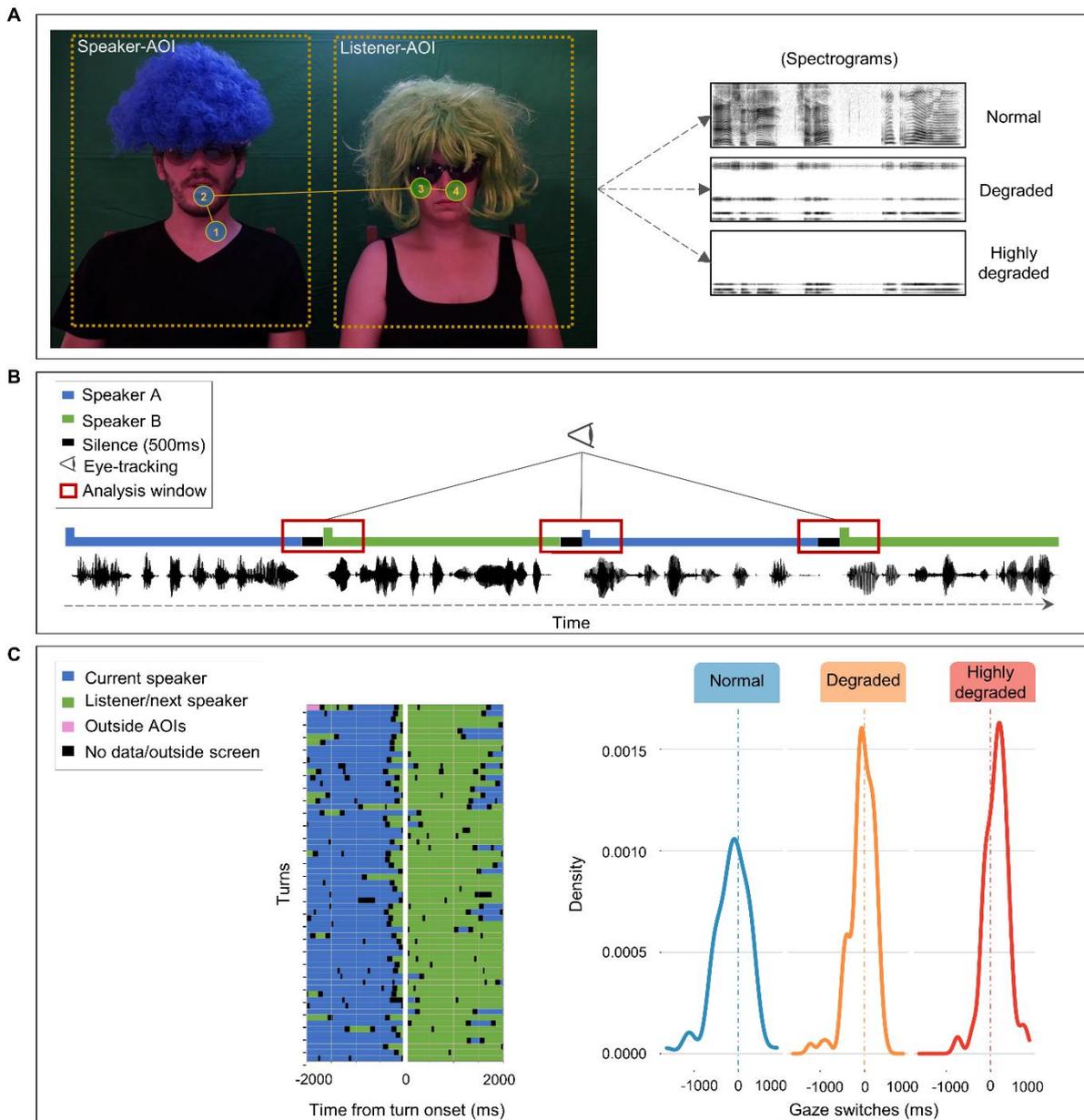
138 For the clarity of the evoked potentials, each turn onset began with a plosive consonant  
139 (although we avoided bilabial to avoid visual cues preceding the plosion). In the stimuli  
140 recording session, all dialogues were written and displayed on a desk in front of the speakers  
141 during 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

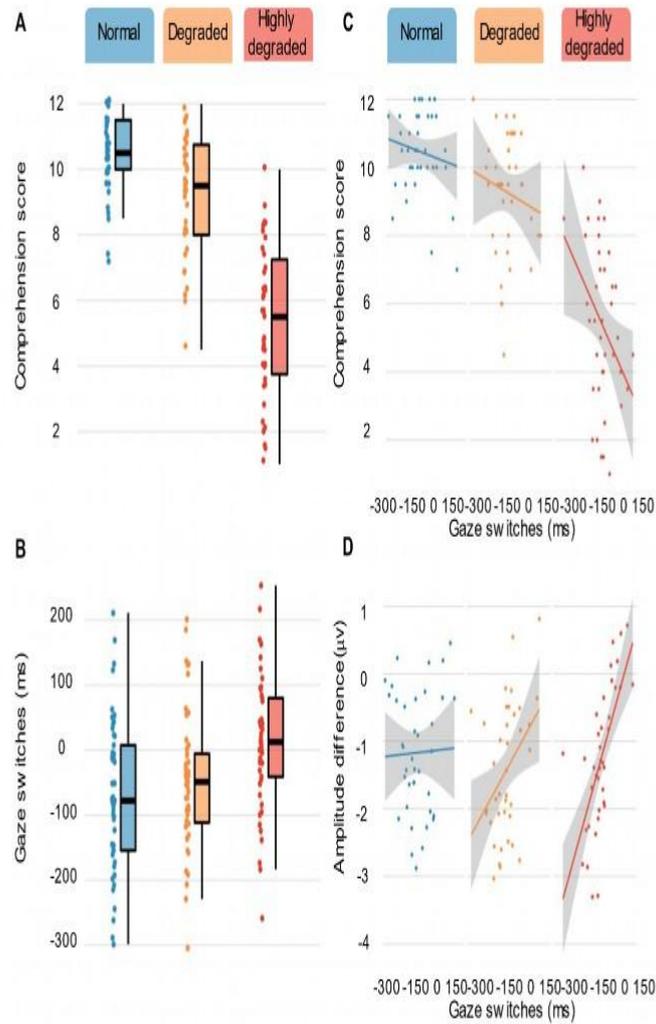
291 As expected, the comprehension score decreases as a function of increasing speech  
292 degradation ( $\beta = -2.551$ , SE = 0.22,  $t = -11.55$ ,  $p < 0.001$ , Figure 2A). Compared to the normal  
293 condition, both the highly degraded and degraded speech conditions altered the  
294 comprehension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

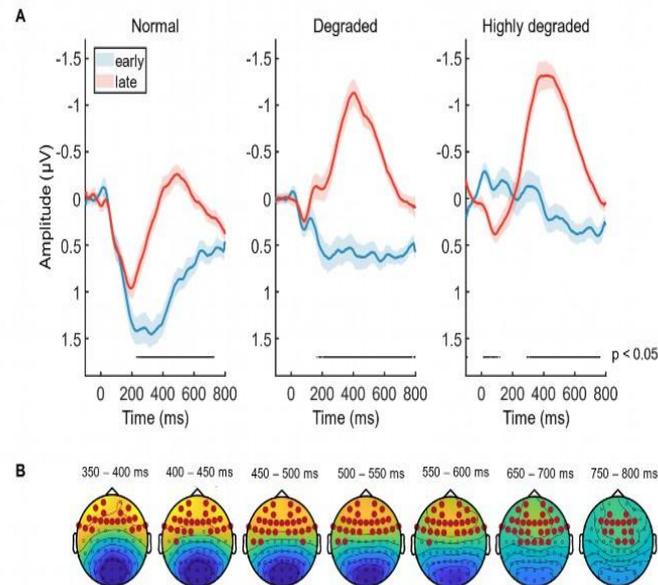
343 The classification of turns on the basis of the latency of gaze switches (**late vs early**) shows a  
344 clear negative component for turns with late switches evolving between 350 and 700ms

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.

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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

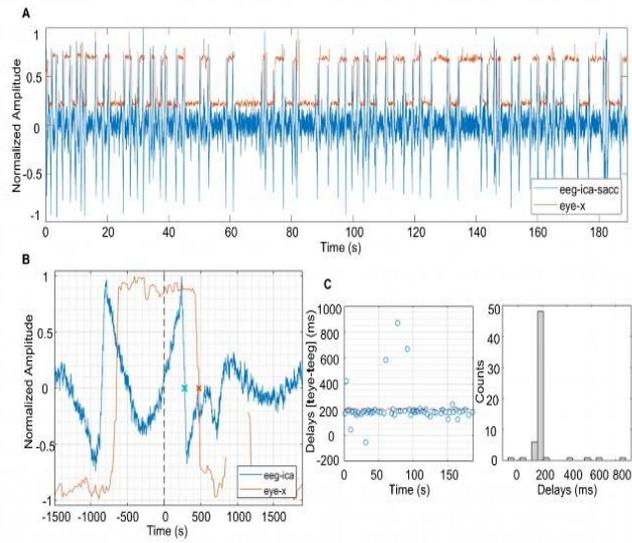
<p>Est-ce que Damien veut attraper une bête avec sa cage ?</p> <p><i>Does Damien want to catch an animal with his cage?</i></p>
<p>Cette cage est faite pour qui ?</p> <p><i>Who is this cage for?</i></p>
<p>Comment Damien arrive à rentrer dans sa cage ?</p> <p><i>How does Damien get into his cage?</i></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

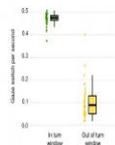
718 Table 2. Exemple of questions for one dialogue.

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.