

1 **Classification:** Biological sciences, Neuroscience

2 **Cortical tracking of speech in noise accounts for reading strategies in children**

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26 **Contributions**

27 M.B., F.D., J.B., X.D., designed the study; F.D., J.B., M.N., M.B. collected the data; F.D., J.B.,
28 M.B., R.A.A.I. analyzed the data; F.D. and M.B. wrote the initial version of the manuscript;
29 and all authors discussed the results and commented on the manuscript.

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- 33 None of the authors disclose any potential conflict of interest.

34 **Abstract (~150 words; now: 184)**

35 Humans' propensity to acquire literacy relates to several factors, among which, the
36 ability to understand speech in noise (SiN). Still, the nature of the relation between reading and
37 SiN perception abilities remains poorly understood. Here, we dissect the interplay between (i)
38 reading abilities, (ii) classical behavioral predictors of reading (phonological awareness,
39 phonological memory and lexical access), and (iii) electrophysiological markers of SiN
40 perception in 99 elementary school children (26 with dyslexia). We demonstrate that cortical
41 representation of phrasal content of SiN relates to the development of the lexical (but not
42 sublexical) reading strategy. In contrast, classical behavioral predictors of reading abilities and
43 the ability to benefit from visual speech to represent the syllabic content of SiN account for
44 global reading performance (i.e., speed and accuracy of lexical and sublexical reading). Finally,
45 we found that individuals with dyslexia properly integrate visual speech information to
46 optimize processing of syntactic information, but not to sustain acoustic/phonemic processing.
47 These results clarify the nature of the relation between SiN perception and reading abilities in
48 typical and dyslexic child readers, and identified novel electrophysiological markers of
49 emergent literacy.

50

51 **Keywords: Cortical tracking of speech, MEG, Reading abilities, Dyslexia, Speech in noise**

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54 Introduction

55 Acquiring literacy is tremendously important in our societies. Central for reading
56 acquisition are adequate phonological awareness,^{1–3} phonological memory,^{4,5} and lexical
57 access.^{6–8} The adequacy of the learning environment also plays a major role.^{9,10} In particular,
58 the presence of recurrent noise in the learning environment can substantially hinder reading
59 acquisition.^{11,12} Therefore, the ability to understand speech in noise (SiN)—which is known to
60 differ between individuals^{13,14}—should modulate the negative impact of environmental noise
61 on reading acquisition. And indeed, the quality of brainstem responses to syllables in noise
62 predicts reading abilities and its precursors.¹⁵ Moreover, individuals with dyslexia often exhibit
63 a SiN perception deficit,^{16,17} that is particularly apparent when the background noise is
64 composed of speech.¹⁸ This deficit has been hypothesized to root in a deficit in phonological
65 awareness,^{19,20} but contradictory reports do exist.²¹ The question of whether SiN processing
66 abilities relate to reading due to a common dependence on classical behavioral predictors (i.e.,
67 phonological awareness, phonological memory and lexical access), or due to other cognitive
68 or neurophysiological processes specific to SiN processing, is thus open. Furthermore, it is also
69 unexplored which aspects of reading and SiN processing abilities are related. Understanding
70 these relations is especially important given that acoustic noise is ubiquitous, and given how
71 adverse dyslexia can be for the cognitive and social development of children.

72 Reading is a multifaceted process. Hence, it is reasonable to think that SiN processing
73 might relate to a restricted set of aspects of reading. Following the Dual Route Cascaded (DRC)
74 model, reading is supported by two different routes: the *sublexical* and the *lexical* routes.^{22,23}
75 The sublexical route implements the grapheme to phoneme conversion. It is used when reading
76 unfamiliar words or pseudowords, but it is not suitable to correctly read irregular words (i.e.,
77 *yacht*) and to acquire fluent reading. Skilled reading relies on the lexical route that supports
78 fast recognition of the orthographic word form of familiar words. The lexical route is

79 indispensable to read irregular words, benefits reading of regular words, and does not
80 contribute to reading pseudowords. Remarkably, the brain would implement these two reading
81 strategies in two distinct neural pathways.^{24–27}

82 There are also several distinct aspects of SiN processing that could relate to reading,
83 and these can be derived from electrophysiological recordings of brain activity during
84 connected speech listening. When listening to connected speech, human auditory cortical
85 activity tracks the fluctuations of speech temporal envelope at frequencies matching the speech
86 hierarchical linguistic structures, i.e., phrases/sentences (0.2–1.5 Hz) and words/syllables (2–8
87 Hz).^{28–38} Such cortical tracking of speech (CTS) is thought to be essential for speech
88 comprehension.^{31,33,35,37,39–41} Corresponding brain oscillations would subserve the
89 segmentation or parsing of incoming connected speech to promote speech
90 recognition.^{31,32,37,39,42} In SiN conditions, children and adults' brain preferentially tracks the
91 attended speech rather than the global auditory scene, though with reduced fidelity when the
92 noise hinders comprehension.^{28,29,38,43–53} Assessing CTS in noise can therefore provide
93 objective measures of the impact of noise on the cortical representation of the different
94 hierarchical linguistic structures of speech. Also relevant is how SiN perception is impacted by
95 noise properties. In essence, the relevant parameters for an acoustic noise in SiN conditions are
96 the degree of energetic and informational masking.⁵⁴ The noise is energetic when its spectrum
97 is similar to that of speech, and non-energetic otherwise. The noise is informational when it is
98 made up of other speech signals, and non-informational otherwise. An energetic noise
99 introduces *physical* interferences and an informational noise introduces *perceptual*
100 interferences. Finally, to enhance SiN processing, humans also benefit from visual information
101 of the speaker's articulatory mouth movements.^{55,56} All these aspects of SiN perception can be
102 captured by measures of CTS.

103 In this study, we investigated the relations between reading abilities, neural
104 representations of SiN quantified with CTS, and classical behavioral predictors of reading in
105 elementary school children. To fully characterize cortical SiN processing, we measured CTS
106 in several types of background noises introducing different levels of energetic and
107 informational masking and in conditions where the face of the speaker was visible (*lips*) or not
108 (*pics*) while talking. This study was designed to answer three major questions: (i) What aspects
109 of cortical SiN processing and reading abilities are related in typically-developing elementary
110 school children (ii) To what extent are these relations mediated by classical behavioral
111 predictors of reading? (iii) Do these relations translate to alterations in dyslexic children in
112 comparison with typical readers matched for age or reading-level? As preliminary steps to
113 tackle these questions, we identify relevant features of CTS in noise, and assessed in a global
114 analysis the nature of the information about reading brought by all the identified features of
115 CTS in noise and classical behavioral predictors of reading abilities.

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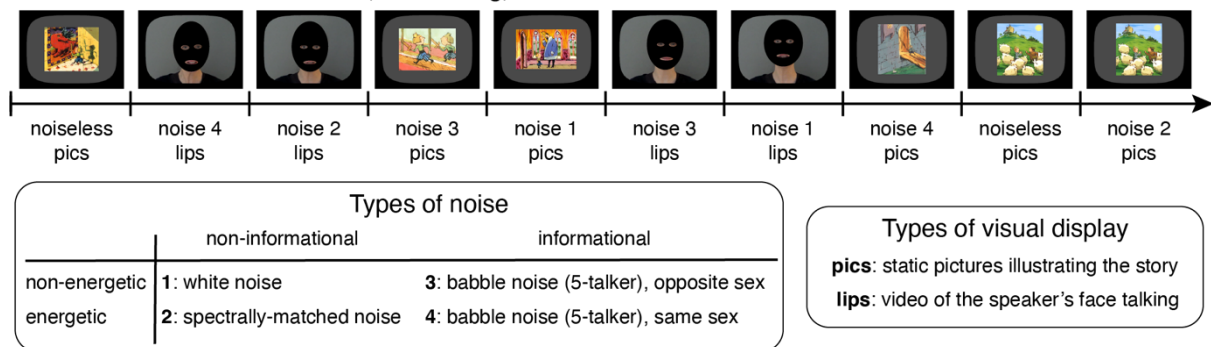
117 **Results**

118 We first report on 73 children with typical reading abilities. Then, we report on 26
119 children with dyslexia matched with a sub-sample of the 73 typical readers for age ($n = 26$) or
120 reading level ($n = 26$). Both control groups were included to tell whether development or
121 reading experience can explain potentially uncovered SiN deficits.⁵⁷ Reading performance and
122 its classical behavioral predictors were characterized in a comprehensive cognitive evaluation
123 (Table 1). Children' brain activity was recorded with magnetoencephalography (MEG) while
124 they were attending to 4 videos of ~6 min each (Figure 1). Each video featured 9 conditions: 1
125 noiseless and 8 SiN resulting from the combination of energetic or non-energetic and
126 informational or non-informational noise with *lips* and *pics* visual inputs. For each condition,
127 we regressed the temporal envelope of the attended speech on MEG signals with several time

128 lags using ridge regression and cross-validation (see methods section for details).⁵⁸ The ensuing
 129 regression model was used to reconstruct speech temporal envelope from the recorded MEG
 130 signal. CTS was computed as the correlation between the genuine and reconstructed speech
 131 temporal envelopes. We did this for MEG and speech envelope signals filtered at 0.2–1.5 Hz
 132 (phrasal rate)^{28,59} and 2–8 Hz (syllabic rate),^{47,51,60,61} and for MEG sensor signals in the left and
 133 right hemispheres separately.

134 Table 2 presents the percentage of the 73 typical readers showing statistically
 135 significant phrasal and syllabic CTS, for both hemispheres, and each condition. All typical
 136 readers showed significant phrasal CTS in noiseless and non-informational (non-speech
 137 hereafter) noise conditions, and still most of them in informational (babble hereafter) noise
 138 conditions (mean \pm SD across conditions, 98.3 ± 2.1 %). Most of the typical readers showed
 139 significant syllabic CTS in noiseless and non-speech noise conditions (93.8 ± 3.2 %), and
 140 slightly less of them in babble noise conditions (80.1 ± 4.3 %). This result clearly indicates that
 141 CTS can be robustly assessed at the subject level.

Time-course of a video stimulus (~6-min long)



142
 143 **Figure 1.** Illustration of the experimental material used in the neuroimaging assessment.
 144 Subjects viewed 4 videos of ~6 min duration. Each video was divided into 10 blocks to which
 145 experimental conditions were assigned. There were 2 blocks of the *noiseless* condition, and 8
 146 blocks of speech-in-noise (SiN) conditions: 1 block for each possible combination of the 4
 147 types of noise and two types of visual display. The interference introduced by the noise was
 148 either energetic or not and informational or not. The visual display provided visual speech
 149 information (*lips*) or not (*pics*).

150 **Table 1.** Mean and standard deviation of behavioral scores in each reading group of 26 children
 151 and comparisons (*t*-tests) between groups. The number of degrees of freedom (*df*) was 50 for
 152 all comparisons except those involving auditory attention (TAP) scores (dyslexic readers vs.
 153 controls in age, *df* = 49; dyslexic readers vs. controls in reading level, *df* = 38) and socio-
 154 economic status (dyslexic readers vs. controls in age, *df* = 49; dyslexic readers vs. controls in
 155 reading level, *df* = 47). IQ, intelligence quotient; RAN, rapid automatized naming; SD, standard
 156 deviation.

	Dyslexic readers		Age-matched control		Reading level control		Dyslexic readers compared with controls			
	Mean	SD	Mean	SD	Mean	SD	in age		in reading level	
							p	t(<i>df</i>)	p	t(<i>df</i>)
Chronological age	9.81	1.26	9.52	0.96	7.21	0.53	0.38	0.89	<0.0001	10.31
Non-verbal IQ	111	11	114	10	112	9	0.30	-1.04	0.784	-0.28
Socio-economic status	6.12	2.44	6.96	1.45	6.96	2.47	0.14	-1.50	0.17	-1.40
Alouette reading accuracy	89.0	5.7	96.2	2.1	89.0	6.46	<0.0001	-6.07	0.988	0.01
Alouette reading speed	141	61	292	91	138	64	<0.0001	-7.04	0.867	0.17
Irregular words reading [words/s]	0.54	0.33	1.16	0.44	0.40	0.35	<0.0001	-5.82	0.15	1.47
Regular words reading [words/s]	0.73	0.41	1.35	0.41	0.61	0.35	<0.0001	-5.51	0.29	1.06
Pseudo-words reading [words/s]	0.42	0.24	0.78	0.30	0.39	0.21	<0.0001	-4.88	0.61	0.50
Visual attention	30.3	3.74	32.0	2.69	27.4	4.43	0.070	-0.95	0.014	2.53
Phoneme suppression	7.92	2.15	9.04	1.75	8.42	1.27	0.046	-2.05	0.313	-1.02
Phoneme fusion	7.73	1.59	9.31	0.97	8.92	1.16	<0.0001	-4.32	0.003	-3.09
Forward digit span	5.08	0.84	5.8	0.69	5.15	0.78	0.001	-3.41	0.735	-0.34
Backward digit span	3.69	0.79	4.5	1.33	3.38	0.75	0.011	-2.66	0.156	1.44
RAN time [s]	24.4	7.84	20.1	3.02	30.6	7.51	0.013	2.59	0.005	-2.91
TAP mean response time [ms]	627	99.0	613	75.4	667	93.4	0.59	0.53	0.07	-1.86
TAP SD response time [ms]	140	45.0	129	30.3	171	46.7	0.33	0.98	0.02	-2.36
TAP correct responses	15.6	0.58	15.7	0.68	15.3	1.07	0.42	-0.81	0.11	1.65
TAP false responses	2.15	2.26	0.84	1.28	1.21	0.97	0.014	2.54	0.89	0.13

157

158 **Table 2.** Percentage of the 73 typical readers showing significant cortical tracking of speech
 159 (CTS) at phrasal and syllabic rates in the 9 different conditions, in the left hemisphere (LH), in
 160 the right hemisphere (RH), or in at least one hemisphere. The two values provided for the
 161 noiseless condition correspond to two arbitrary subdivisions of the *noiseless* data to match the
 162 amount of data for the eight noise conditions.

	Phrasal CTS									
	Noiseless		Non-Informational Noise				Informational Noise			
			Non-energetic		Energetic		Non-energetic		Energetic	
	Pics	Lips	Pics	Lips	Pics	Lips	Pics	Lips	Pics	Lips
Left hemisphere	100	100	100	100	100	100	91.8	97.3	90.4	97.3
Right hemisphere	100	100	100	100	100	100	94.5	98.6	90.4	95.9
At least one hemisphere	100	100	100	100	100	100	97.3	100	95.9	100
	Syllabic CTS									
Left hemisphere	89	84.9	82.2	83.6	82.2	86.3	53.4	65.7	49.3	61.6
Right hemisphere	91.8	89	89	91.8	86.3	91.8	69.9	76.7	67.1	76.7
At least one hemisphere	97.3	94.5	94.5	94.5	87.7	94.5	78.1	86.3	76.7	79.4

163

164 **What aspects of SiN processing modulate the measures of CTS in noise?**

165 First, we identify the main factors modulating CTS in SiN conditions. To that aim, we
166 evaluated with linear mixed-effects modeling how the normalized CTS (nCTS) in SiN
167 conditions depends on hemisphere, noise properties, and visibility of the talker's lips. The
168 nCTS is a contrast between CTS in SiN and noiseless conditions (see Methods) that takes
169 values between -1 and 1 , with negative values indicating that the noise reduces CTS. Such
170 contrast presents the advantage of being specific to SiN processing abilities by factoring out
171 the global level of CTS in the noiseless condition. In that analysis, nCTS values were corrected
172 for age, time spent at school and IQ.

173 Table 3 presents the final linear mixed-effects model of phrasal and syllabic nCTS, and
174 Figure 2 illustrates underlying values.

175 The pattern of how nCTS changed with different types of noises was overall similar for
176 phrasal and syllabic nCTS. Non-speech noise did not substantially change CTS (nCTS was
177 close to 0). However, babble noise resulted in a substantial reduction of CTS compared to the
178 noiseless condition for both hemispheres and irrespective of the availability of visual speech
179 information. That is, nCTS in babble noise conditions was roughly between -0.1 and -0.3 ,
180 indicating that CTS in babble noise was 20–50% (values obtained by inverting the formula of
181 nCTS) lower than CTS in noiseless conditions.

182 Availability of visual speech information (*lips* conditions) increased the level of nCTS
183 only in babble noise conditions for phrasal nCTS, and in all noise conditions for syllabic nCTS.

184 And finally, the noise impacted differently nCTS in the left and right hemispheres. The
185 phrasal nCTS was higher in the left than right hemisphere in babble noise conditions. It was
186 the other way round for syllabic nCTS in all noise conditions.

187 In summary, the CTS is mostly impacted by informational noises, and is also modulated
188 by the availability of visual speech and the hemisphere (only in informational noise conditions

189 for phrasal CTS, and in all noise conditions for syllabic CTS). These observations guided the
190 elaboration of 8 relevant features (contrasts) of nCTS in SiN conditions (see Supplementary
191 Methods): the global level of nCTS and its informational, visual and hemispheric modulations,
192 all for phrasal and syllabic nCTS. In the next sections we unravel the associations between
193 these features, reading abilities, and classical behavioral predictors of reading.

194

195 **Table 3.** Factors included in the final linear mixed-effects model fit to the normalized cortical
196 tracking of speech (nCTS) at phrasal and syllabic rates. Factors are listed in their order of
197 inclusion.

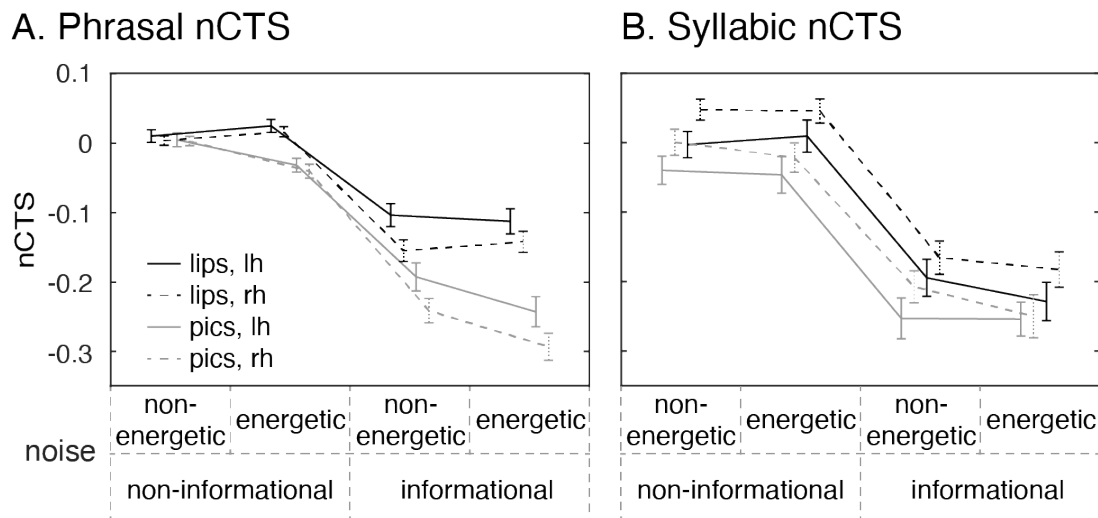
	χ^2		p
	df	value	
phrasal nCTS			
noise	3	597.50	< 0.0001
visual	1	127.28	< 0.0001
hemisphere	1	17.27	< 0.0001
noise × visual	3	67.70	< 0.0001
noise × hemisphere	3	10.98	0.012
syllabic nCTS			
noise	3	340.61	< 0.0001
visual	1	21.42	< 0.0001
hemisphere	1	10.38	0.0013

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203 **Figure 2.** Impact of the main fixed-effects on the normalized cortical tracking of speech
204 (nCTS) at phrasal (A) and syllabic rates (B). Mean and SEM values are displayed as a function
205 of noise properties. The four traces correspond to visual conditions with the speaker's talking
206 face visible (*lips*; black traces) and with static pictures illustrating the story (*pics*; gray traces),
207 within the left (*lh*; connected traces) and right (*rh*; dashed traces) hemispheres. nCTS values
208 are bounded between -1 and 1 , with values below 0 indicating lower CTS in speech-in-noise
209 conditions than in noiseless conditions.

210

211 **What is the nature of the information about reading abilities brought by measures of SiN**
212 **processing and classical behavioral predictors of reading?**

213 Having identified relevant features of cortical SiN processing, we first evaluated to
214 which extent these features and classical behavioral predictors of reading bring information
215 about reading abilities. More precisely, we used partial information decomposition (PID) to
216 dissect the information about reading abilities (target) brought by behavioral scores (first set of
217 explanatory variables) and features of the nCTS in noise (second set of explanatory
218 variables).⁶²⁻⁶⁴ Generally speaking, PID can reveal to which extent two sets of explanatory
219 variables bring unique information about a target (information present in one set but not in the
220 other), redundant information (information common to the two sets), and synergistic
221 information (information emerging from the interaction of the two sets). Here, the target
222 consisted of 5 reading scores: (i) an accuracy and (ii) a speed score for the reading of a

223 connected meaningless text (Alouette test), and scores (number of correctly read words per unit
224 of time) for the reading of a list of (iii) irregular words, (iv) regular words and (v) pseudowords.
225 The first set of explanatory variables consisted of a total of 5 measures indexing phonological
226 awareness (scores on phoneme suppression and fusion tasks), phonological memory (scores on
227 forward and backward digit repetition), and lexical access (rapid automatized naming (RAN)
228 score). The second set of explanatory variables was the 8 features of nCTS in SiN conditions
229 identified in the previous subsection. Again, in that analysis, all measures were corrected for
230 age, time spent at school and IQ.

231 As a result, features of nCTS in noise brought significant unique information about
232 reading abilities (unique information = 0.61; $p = 0.016$), while classical behavioral predictors
233 did not (unique information = 0.31; $p = 0.10$). Both sets of explanatory variables brought
234 significant redundant but not synergistic information about reading (redundant information =
235 0.16; $p = 0.0020$; synergistic information = 0.12; $p = 0.26$).

236 These results indicate that the way the CTS is impacted by ambient noise relates to
237 reading abilities in a way that is not fully explained by classical behavioral predictors of
238 reading. Further analyses will therefore strive to identify which aspects of SiN processing and
239 reading are related, and which of these relations are mediated by classical behavioral predictors
240 of reading.

241

242 **Which features of SiN processing relate to reading abilities in a way that is not mediated** 243 **by classical behavioral predictors of reading?**

244 We next identified with linear mixed-effects modeling (i) the set of classical behavioral
245 predictors of reading that best explains reading abilities, and (ii) the set of features of nCTS in
246 noise that brings additional information about reading abilities. Importantly, all measures were
247 corrected for age, time spent at school, and IQ, and further standardized. In that analysis, the

248 type of reading score used to assess reading abilities was taken as a factor. Classical behavioral
249 predictors of reading (5 measures) were first entered as regressors, before considering the
250 features of nCTS in noise (8 measures) as additional regressors.

251 Table 4 presents the final linear mixed-effects model fit to reading scores. It shows that
252 lexical access (indexed by RAN score) and phonological memory (indexed by the forward digit
253 span) relate to global reading abilities. It also shows that two aspects of SiN processing, the
254 visual and informational modulations in phrasal nCTS, explain a different part of the variance
255 in reading abilities. Importantly, these two indices relate to reading in a way that depend on the
256 type of reading score. These effects are illustrated with simple Pearson correlations in Table 5.
257 The time necessary to fulfil the *RAN* task was significantly negatively correlated with all
258 reading scores. The *forward digit span* was significantly positively correlated with all reading
259 scores. The visual modulation in phrasal nCTS was overall positively correlated with scores
260 involving reading speed (Alouette speed score and regular-, irregular- and pseudoword reading
261 scores; significantly so for pseudoword reading only) but not with the Alouette accuracy score.
262 The informational modulation in phrasal nCTS was characterized by a significant positive
263 correlation with the score on irregular word reading only. Interestingly, the correlation was not
264 significant—and even negative—with the score on pseudoword reading.

265 We will now attempt to better understand the meaning of this last association (between
266 the informational modulation in phrasal nCTS and irregular- but not pseudoword reading).
267 Given that different routes support reading of irregular words (lexical route) and pseudowords
268 (sublexical route), the contrast between corresponding standardized scores (irregular
269 – pseudowords) indicates reading strategy. We henceforth refer to this index as the reading
270 strategy index. Further strengthening the correlation pattern highlighted above for the
271 informational modulation in phrasal nCTS, this latter index correlated even more strongly with
272 the reading strategy index ($r = 0.44, p < 0.0001$; See Fig. 3, left) than with the score on irregular

273 word reading. This suggests that irregular and pseudoword reading scores bring synergistic
274 information about the informational modulation in phrasal nCTS. To confirm this, we used
275 partial information decomposition (PID) to dissect the information about the informational
276 modulation in phrasal nCTS (target) brought by irregular reading scores (first explanatory
277 variable) and pseudoword reading scores (second explanatory variable). This analysis revealed
278 that the score on irregular word reading carried significant unique information about the
279 informational modulation in phrasal nCTS (unique information = 0.044, $p = 0.015$), while the
280 score on pseudowords did not (unique information = 0.0001, $p = 0.62$), and most interestingly,
281 that these two reading scores carried significant synergistic but not redundant information
282 about the informational modulation in phrasal nCTS (redundant information = 0.0019, $p = 0.44$;
283 synergistic information = 0.146, $p < 0.0001$).

284 Figure 3 (right panel) further illustrates that the reading strategy index was correlated
285 with phrasal nCTS only in the informational noise conditions.

286 In summary, classical behavioral predictors of reading were informative about global
287 reading abilities (similar correlation with all 5 measures of reading), while two aspects of the
288 CTS in noise (informational and visual modulations in phrasal nCTS) related to specific aspects
289 of reading (correlation with some but not all 5 measures of reading). The extent to which visual
290 speech boosts phrasal CTS in noise was related to reading speed but not accuracy, and the
291 ability to maintain adequate phrasal CTS in babble noise related to reading strategy (dominant
292 reliance on the lexical rather than sublexical route).

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299 **Table 4.** Regressors included in the final linear mixed-effects model fit to the 5 reading scores
 300 taken as factors. Regressors are listed in their order of inclusion.

	χ^2		p
	df	value	
RAN	1	15.79	< 0.0001
forward digit span	1	11.10	0.0009
visual modulation in phrasal nCTS	1	4.85	0.028
informational modulation in phrasal nCTS dependant on reading score	5	15.63	0.0080
visual modulation in phrasal nCTS dependant on reading score	4	11.09	0.026

301

302

303 **Table 5.** Pearson correlation between measures of reading abilities and relevant brain and
 304 behavioral measures. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, # $p < 0.1$. nCTS, normalized
 305 cortical tracking of speech.

	RAN	forward digit span	Visual modulation in phrasal nCTS	Informational modulation in phrasal nCTS	Visual modulation in syllabic nCTS	Phoneme suppression	Phoneme fusion
Alouette accuracy	-0.37 **	0.33 **	0.00	-0.35	0.29 *	0.11	0.25 *
Alouette speed	-0.41 ***	0.38 ***	0.21 #	0.08	0.30 **	0.31 **	0.30 **
Irregular words	-0.35 **	0.42 ***	0.18	0.26 *	0.37 **	0.21 #	0.17
Regular words	-0.42 ***	0.35 **	0.18	0.12	0.31 **	0.25 *	0.19
Pseudowords	-0.34 **	0.30 *	0.31 **	-0.07	0.23 *	0.21 #	0.11

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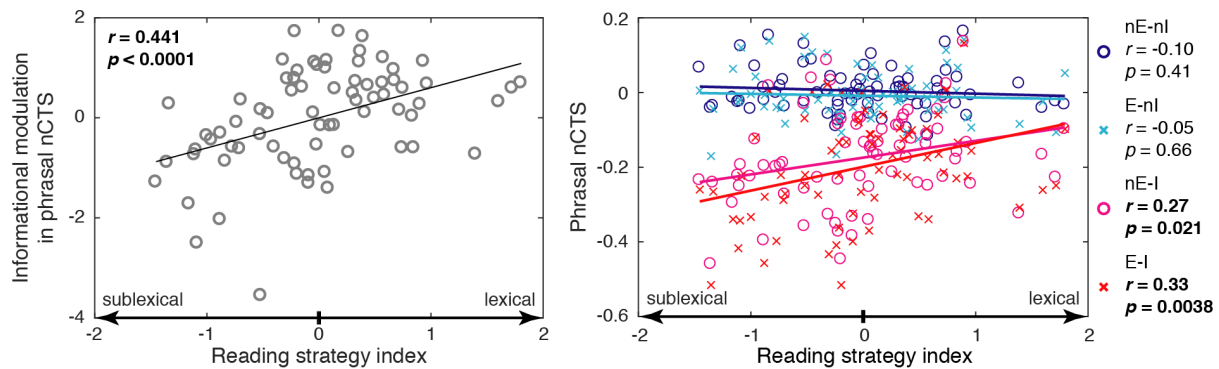
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Relation between the reading strategy index and phrasal nCTS



314

315 **Figure 3.** Relation between the reading strategy index and the normalized cortical tracking of
 316 speech (nCTS) at phrasal rate. **Left** — The informational modulation in phrasal nCTS as
 317 function of the reading strategy index. Gray circles depict participants' values and a black trace
 318 is the regression line, with correlation and significance values indicated in the bottom right
 319 corner. **Right** — The mean nCTS across visual conditions and both hemispheres for the 4 types
 320 of noise: energetic (*E*) or not (*nE*) and informational (*I*) or not (*nI*), with *nE-nI* in blue, *E-nI* in
 321 turquoise, *nE-I* in red and *E-I* in pink. Circles (*nE* noise conditions) and crosses (*E*) depict
 322 participants' values, and full traces are the regression lines. Correlation and significance level
 323 for all noise conditions are indicated on the right of each plot.

324

325 **Do other features of SiN processing or classical behavioral predictors of reading relate to**
 326 **reading abilities?**

327 Above, we have identified a set of brain and behavioral measures related to reading.
 328 Importantly, each measure was included because it explained a new part of the variance in
 329 reading abilities. But the first PID analysis revealed that brain and behavioral measures do carry
 330 significant redundant information. This means that some measures might have been left aside
 331 if they explained some variance that was already explained (i.e., if they provided mainly
 332 redundant information). Accordingly, we also ran the linear mixed-effects analysis with nCTS
 333 and behavioral regressors that were not included. This analysis identified an overall positive
 334 correlation between reading abilities and (i) the visual modulation in syllabic nCTS ($\chi^2(1) =$
 335 $9.74, p = 0.0018$), (ii) phoneme suppression ($\chi^2(1) = 4.94, p = 0.026$) and (iii) phoneme fusion

336 ($\chi^2(1) = 4.00, p = 0.038$). Corresponding Pearson correlation coefficients are presented in
337 Table 5. A detailed PID analysis revealed that these “side” measures were redundant—and
338 synergistic to some extent—with RAN and forward digit span but not with visual and
339 informational modulations in phrasal nCTS (see Supplementary Results).

340 In summary, scores indexing phonological awareness (score on phoneme suppression
341 and phoneme fusion) and the extent to which visual speech boosts syllabic CTS in noise (visual
342 modulation in syllabic nCTS) relate to global reading abilities in a way that is mediated by the
343 main classical behavioral predictors of reading we identified (RAN and forward digit span) but
344 not with visual and informational modulations in phrasal nCTS

345

346 **Does phonological awareness mediate SiN perception capacities?**

347 Having identified three relations between various aspects of cortical SiN processing
348 and reading, we now specifically test the hypothesis that each of these relations is mediated by
349 phonological awareness. For that, we again relied on PID to decompose the information about
350 reading abilities (target) brought by each identified feature of the CTS in noise (first
351 explanatory variable) and the mean of the two scores indexing phonological awareness (second
352 explanatory variable). Ensuing results are provided in Table S1. In summary, phonological
353 awareness mediated one aspect of the relation between reading and cortical SiN processing
354 (relation with the benefit of visual speech to boost syllabic CTS in noise), but not the two others
355 (relations involving phrasal CTS in noise).

356

357 **Do relations between reading and features of nCTS translate to alterations in dyslexia?**

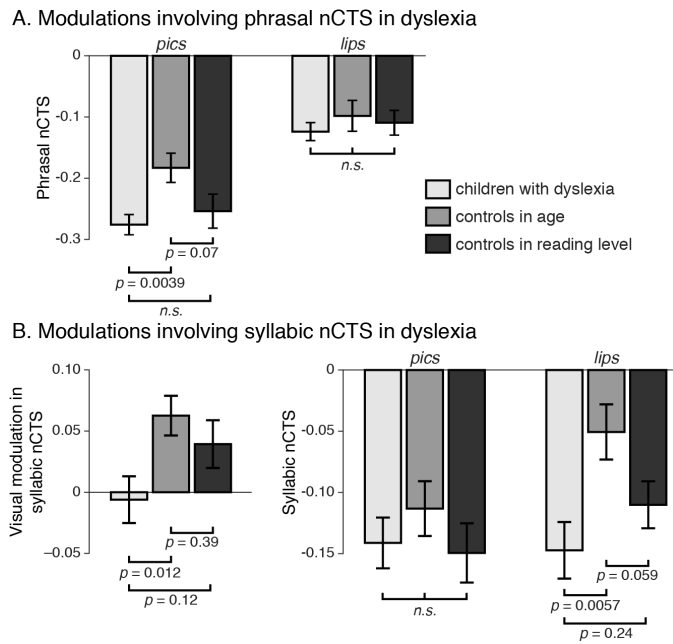
358 We next evaluated whether the relations between features of nCTS and reading abilities
359 translate to alterations in dyslexia. That analysis was conducted on a group of 26 dyslexic

360 readers, 26 age-matched and 26 reading-level-matched typically developing children selected
361 among the 73 children included in the first part of the study.

362 Based on the result that reading abilities relate to phrasal nCTS in informational noise
363 and to the boost in nCTS brought by visual speech, we focused the comparison on the phrasal
364 nCTS in *lips* and *pics* averaged across hemispheres and babble noise conditions (see Fig. 4A).
365 As a result, individuals with dyslexia had significantly lower phrasal nCTS than age-matched
366 controls in *pics* ($t(50) = 3.03, p = 0.0039$) but not in *lips* ($t(50) = 0.83, p = 0.41$). This difference
367 was not present in the comparison with reading-level-matched controls (*pics*, $t(50) = 0.65, p =$
368 0.52 ; *lips*, $t(50) = 0.54, p = 0.59$).

369 Based on the result that reading abilities relate to the visual modulation in syllabic
370 nCTS, we focused the comparison on this index (see Fig. 4B left part). This revealed that
371 individuals with dyslexia had significantly lower visual modulation in syllabic nCTS than age-
372 matched ($t(50) = 2.62, p = 0.012$) but not reading-level-matched controls ($t(50) = 1.59, p =$
373 0.12). To better understand the nature of this difference, we further compared between groups
374 the syllabic nCTS in *lips* and *pics* averaged across hemispheres and noise conditions (see Fig.
375 4B right part). As a result, individuals with dyslexia had significantly lower syllabic nCTS than
376 age-matched controls in *lips* ($t(50) = 2.89, p = 0.0057$) but not in *pics* ($t(50) = 0.88, p = 0.38$).
377 This difference was not present in the comparison with reading-level-matched controls (*lips*,
378 $t(50) = 1.19, p = 0.24$; *pics*, $t(50) = 0.25, p = 0.81$).

379 In summary, one aspect of cortical SiN processing (reliance on visual speech to boost
380 phrasal nCTS) was not altered in dyslexia while two other aspects (phrasal nCTS in babble
381 noise, and reliance on visual speech to boost syllabic nCTS) were altered in dyslexia in
382 comparison with typical readers matched for age but not reading level. This suggests that these
383 two later aspects are altered as a consequence of reduced reading experience.



384

385 **Figure 4.** Comparison between children with dyslexia and controls in the measures of
 386 normalized cortical tracking of speech (nCTS) significantly related to reading abilities. **A**
 387 — Modulations involving phrasal nCTS. Displayed are the mean and SEM within groups
 388 (dyslexia, control in age, and control in reading level) of phrasal nCTS in the conditions with
 389 (*lips*) and without (*pics*) visual speech information. Values of nCTS were averaged across
 390 hemispheres and informational noise conditions for phrasal nCTS and across hemispheres and
 391 all noise conditions for syllabic nCTS. **B** — Modulations involving syllabic nCTS. On the left
 392 is the visual modulation in syllabic nCTS. The right part is as in A.

393

394 Discussion

395 The main objective of this study was to fully characterize the nature of the relation
 396 between objective cortical measures of SiN processing and reading abilities in elementary-
 397 school children. Results demonstrate that some cortical measures of SiN processing relate to
 398 reading performance and reading strategy. First, phrasal nCTS in babble (*i.e.*, informational)
 399 noise relates to the ability to read irregular but not pseudowords, which in the DRC model
 400 indicates maturation of the lexical route. Second, the ability to leverage visual speech to boost
 401 phrasal nCTS in babble noise relates to reading speed (but not accuracy). Third, the ability to
 402 leverage visual speech to boost syllabic nCTS in noise relates to global reading abilities. Fourth,

403 classical behavioral predictors of reading abilities (RAN, phonological memory and
404 phonological awareness) relate to global reading performance, and not strategy. Importantly,
405 behavioral scores and the two features of phrasal CTS in babble noise explained a different part
406 of the variance in reading abilities. Finally, the first and third relations uncovered in typical
407 readers translated to significant alteration in dyslexia in comparison with aged-matched but not
408 reading-level-matched typically developing children. Two limitations are discussed in
409 Supplementary Discussion.

410 Significant associations were found between reading abilities and some features of
411 phrasal and syllabic nCTS. There is evidence that CTS at phrasal rate (here taken as 0.2–1.5
412 Hz) partly reflects parsing or chunking of words, phrases and sentences.⁶⁵ Indeed, the brain
413 tracks phrase and sentence boundaries even when speech is devoid of prosody but only if it is
414 comprehensible,³⁹ and the phase of below-4-Hz brain oscillations modulates perception of
415 ambiguous sentences.³⁷ CTS at phrasal/sentential rate would help align neural excitability with
416 syntactic information to optimize language comprehension.³⁶ In contrast, CTS at syllable rate
417 (here taken as 2–8 Hz) would reflect low level auditory processing.⁶⁵ In light of the above, our
418 results highlight that associations between SiN perception and reading abilities build on their
419 shared reliance on both language processing and low-level auditory processing.

420

421 **Robustness of cortical speech representation to babble noise indexes the development of** 422 **the lexical route**

423 Our results indicate that an objective cortical measure of the ability to deal with babble
424 noise relates to the maturation of the lexical route. Technically, the informational modulation
425 in phrasal nCTS correlated significantly positively with the reading score on irregular but not
426 pseudowords. Reading score on irregular words indeed provided unique information about the
427 informational modulation in nCTS. Also, the two reading scores in synergy provided some

428 additional information about the informational modulation in nCTS. Furthermore, the result
429 that the informational modulation in nCTS correlated more with the reading strategy index than
430 the score on the irregular words suggests that the key elements at the basis of this relation are
431 the processes needed to read irregular words that are not needed to read pseudo-words. Our
432 results in dyslexia support this relation although they cannot rule out the possibility that it is
433 due to variability in reading experience since phrasal nCTS in non-visual informational noise
434 conditions was reduced in dyslexic readers compared with age-matched but not reading-level-
435 matched controls.

436 The relation between the development of the lexical route and the level of phrasal nCTS
437 in babble noise could be explained by a positive influence of good SiN abilities on reading
438 acquisition. Let us take as an example the situation of being faced for the first time with a
439 written word that is read by a teacher while some classmates are making noise. SiN abilities
440 will naturally determine the odds of hearing that word properly and hence the odds of building
441 up the orthographic lexicon. When reading again the word alone, only children with good SiN
442 abilities will have the opportunity to train their lexical route for that specific word. Of course
443 the same chain of action could be posited for the training of grapheme–phoneme
444 correspondence. But there are many more words than phonemes and syllables, so that good
445 SiN abilities might be more important to successfully learn the correspondence between
446 irregular words’ orthographic and phonological representations. Indeed, grapheme–phoneme
447 correspondence is intensively trained when learning to read. Children are repeatedly exposed
448 to examples of successful grapheme–phoneme correspondence, some with noise, and some
449 without noise. Accordingly, no matter what children’s SiN abilities are, they will learn the
450 grapheme–phoneme correspondence and develop their sublexical route, provided that they
451 have adequate phonological awareness. Supporting this, phonological awareness does not
452 predict SiN abilities in typical readers.²¹

453 Alternatively, the relation between the ability to read irregular words (which tags the
454 development of the lexical route) and nCTS in babble noise could be mediated by the degree
455 of maturation of the mental lexicon.^{66,67} The mental lexicon integrates and binds the
456 orthographic, semantic and phonological representations of words. Its proper development is
457 important for reading acquisition. Indeed, reading acquisition entails creating a new
458 orthographic lexicon and binding it to the preexisting semantic and phonological lexicons.⁶⁸
459 Development of such binding (i) is indispensable to read irregular words,⁶⁹ (ii) benefits reading
460 of regular words, and (iii) does not contribute to reading pseudowords. The proper development
461 of the mental lexicon is also important for SiN comprehension. Indeed, SiN comprehension
462 strongly depends on vocabulary knowledge.^{21,70,71} And the level of CTS in noise relates to the
463 listeners' level of comprehension.^{35,40,41} This therefore suggests that the robustness of CTS to
464 babble noise depends on the level of comprehension, which in turn depends on how developed
465 is the mental lexicon. The development of the mental lexicon could therefore be the hidden
466 factor mediating the relation between SiN and lexical reading ability. This is also perfectly in
467 line with our result that altered phrasal nCTS in babble noise in dyslexia may result from
468 reduced reading experience. In brief, reading difficulties in dyslexia would reduce their reading
469 experience, which would impair building up the mental lexicon, and in turn impede SiN
470 perception. Still, future studies on the association between SiN processing and reading should
471 include measures of the development of the mental lexicon to carefully analyse the interrelation
472 between SiN perception, reading abilities and the development of the mental lexicon.

473

474 **Audiovisual integration and reading abilities**

475 We found significant relations between reading abilities and the ability to leverage
476 visual speech to maintain phrasal and syllabic CTS in noise. Visual speech cues (articulatory
477 mouth and facial gestures) are well known to benefit SiN comprehension⁵⁵ and CTS in noise.⁷²⁻

478 ⁷⁶ Obviously, the auditory signal carries much more fine-grained information about the
479 phonemic content of speech than the visual signal. But the effect of audiovisual speech
480 integration is quite evident in SiN conditions, where it affords a substantial comprehension
481 benefit.^{55,56,77,78} Mirroring this perceptual benefit, it is already well documented that phrasal
482 and syllabic CTS in noise is boosted in adults when visual speech information is available.<sup>72–
483 76,79–82</sup>

484 We found that the visual modulation in phrasal nCTS correlated globally positively
485 with reading speed (significantly so for the pseudowords) but not accuracy. However, our
486 dyslexic readers (compared with both control groups) did not have any alteration in their
487 phrasal nCTS in babble noise when visual speech was provided. Instead, they successfully
488 relied on visual speech information to restore their phrasal CTS in babble noise (which was
489 altered without visual speech information). In other words, reliance on lip-reading to maintain
490 appropriate phrasal CTS in babble noise appeared as a protection factor in our group of dyslexic
491 readers.

492 We also found that the visual modulation in syllabic nCTS correlated globally
493 positively with reading abilities. More interestingly, our dyslexic readers (compared with both
494 control groups) did not have any significant alteration in their syllabic nCTS in noise when
495 visual speech was not provided. However, compared with age-matched typically developing
496 children, they benefited significantly less from visual speech to boost syllabic CTS in noise.
497 Instead, they behaved more like reading-level-matched typically developing children.
498 Accordingly, our results cannot argue against the view that poor audiovisual integration in
499 dyslexia is caused by reduced reading experience.^{57,83,84} Notwithstanding, the pattern of results
500 (see Fig. 4B left) is even suggestive of an alteration in dyslexia in comparison with reading-
501 level-matched children. More statistical power would be needed to confirm/infirm the trend.

502 Our result that audiovisual integration abilities correlate with reading abilities is in line
503 with existing literature. Indeed, individuals with dyslexia benefit less from visual cues to
504 perceive SiN than typical readers^{85–89}. Audiovisual integration and reading could be altered in
505 dyslexia simply because both rely on similar mechanisms. Indeed, reading relies on the ability
506 to bind visual (graphemic) and auditory (phonemic) speech representations.^{90,91} And according
507 to some authors, suboptimal audiovisual integration mechanisms could reduce reading
508 fluency.⁹² Importantly, the finding that individuals with dyslexia benefit normally from visual
509 speech to boost phrasal but not syllabic CTS in noise brings important information about the
510 nature of the audiovisual integration deficit in dyslexia. Following the functional roles
511 attributed to CTS, individuals with dyslexia would properly integrate visual speech information
512 to optimize processing of syntactic information,³⁶ but not to support acoustic/phonemic
513 processing.⁶⁵ This could be explained by their preserved ability to extract and integrate the
514 temporal dynamics of visual speech, but not the lip configuration,⁸⁹ two aspects of audiovisual
515 speech integration currently thought to be supported by distinct neuronal pathways.⁹³ This
516 inability to rely on lip configuration to improve auditory phonemic perception in SiN
517 conditions may be caused by a supra-modal phonemic categorization deficit, as already
518 proposed for children with specific language impairment.⁹⁴ Finally, the fact that the visual
519 modulation in syllabic nCTS brought a limited amount of unique information about reading
520 with respect to classical behavioral predictors of reading, but that all of them brought more
521 information in synergy, suggests that a broad set of low-level processing abilities contribute to
522 determine reading abilities and alterations in dyslexia.^{95,96}

523

524 **Classical behavioral predictors related to global reading abilities**

525 Our results confirm that classical behavioral predictors of reading (RAN, phonological
526 memory, and metaphonological abilities) are directly related to the global reading level rather

527 than reading strategy. We draw this conclusion since the optimal model for reading score
528 contained a common slope for all reading subtests. This means that the model was not
529 significantly improved by optimizing the slope for each of the 5 reading subtests separately.
530 Accordingly, univariate correlation coefficients presented in Table 5 were roughly similar
531 across the 5 reading scores.

532 Phonological memory (assessed with forward digit span) was significantly positively
533 correlated with the global reading level. That phonological memory relates to global reading
534 abilities rather than reading strategy is well documented.⁴ Poor readers, regardless of their
535 reading profile, typically perform poorly on phonological memory tests involving digits,
536 letters,^{97,98} or words.⁹⁹

537 Performance on the RAN task was also related to the global reading level, in line with
538 existing literature.^{6-8,100-103} RAN performance has indeed a moderate-to-strong relationship
539 with all classical reading measures alike, including word, non-word and text reading, as well
540 as text comprehension.¹⁰⁰ It is a consistent predictor of reading fluency in various alphabetic
541 orthographies independently of their complexity.¹⁰⁴ RAN performance even predicts reading
542 performance at 2 years interval,¹⁰⁵ similarly well for reading performance assessed with tasks
543 tagging lexical and sublexical routes. It is thought that RAN and reading performances correlate
544 because both involve serial processing and oral production,¹⁰³ two processes that are common
545 to both reading routes.

546 Finally, phonological awareness assessed with phoneme suppression and fusion tasks
547 was significantly related to reading abilities. However, the information it brought about reading
548 was less, and essentially redundant with that brought by RAN and phonological memory. This
549 is not surprising given that children tested in the present study had at least one year of reading
550 experience. Phonological awareness indeed plays a key role in the early stages of reading

551 acquisition, i.e., when learning grapheme-to-phoneme conversion,^{106–108} and undergoes a
552 substantial maturation during that period.¹⁰⁹

553

554 **Phonological awareness**

555 Our results indicate that, in typical readers, phonological awareness mediates at best
556 part of the relation between the cortical processing of SiN and reading abilities. Indeed, the
557 information about reading brought by phonological awareness was redundant with that brought
558 by the visual modulation in syllabic nCTS, but not with that brought by the informational and
559 visual modulations in phrasal nCTS. This finding illustrates the importance of separating the
560 different processes involved in SiN processing and reading to seek associations. It also provides
561 a potential reason why contradictory reports exist on the topic.^{19–21}

562

563 **Conclusion**

564 Overall, these results significantly further our understanding of the nature of the relation
565 between SiN processing abilities and reading abilities. They demonstrate that cortical
566 processing of SiN and reading abilities are related in several specific ways, and that some of
567 these relations translate into alterations in dyslexia that are attributable to reading experience.
568 They also demonstrate that classical behavioral predictors of reading (including phonological
569 awareness) mediate relations involving the processing of acoustic/phonemic but not syntactic
570 information in natural SiN conditions. This contrasts with the classically assumed mediating
571 role of phonological awareness. Instead, the ability to process speech syntax in babble noise
572 could directly modulate skilled reading acquisition. Finally, the information about reading
573 abilities brought by cortical markers of syntactic processing of SiN was complementary to that
574 provided by classical behavioral predictors of reading. This implies that such markers of SiN
575 processing could serve as novel electrophysiological markers of reading abilities.

576 **Material and Methods**

577 **Participants**

578 Seventy-three typical and 26 dyslexic readers enrolled in elementary-school took part
579 in this experiment (see Table 1 for participants' characteristics). All were native French
580 speakers, reported being right-handed, had normal hearing according to pure tone audiometry
581 (normal hearing thresholds between 0–25 dB HL for 250, 500, 1000, 2000, 4000 and 8000 Hz)
582 and normal SiN perception as revealed by a SiN test (Lafon 30) from a French language central
583 auditory battery.¹¹⁰ We used a French translation of the Family Affluence Scale ¹¹¹ to evaluate
584 participants' socio-economic level.

585 This study was approved by the Ethics Committee of the CUB Hôpital Erasme
586 (Brussels, Belgium). Participants and their legal representatives signed a written informed
587 consent before participation. Participants were compensated with a gift card worth 50 euros.

588

589 **Behavioral assessment**

590 Participants underwent a comprehensive behavioral assessment intended to appraise
591 their reading abilities and some cognitive abilities related to reading or speech perception.

592

593 ***Reading abilities***

594 Children completed the word reading (regular, irregular and pseudowords) tasks of a
595 dyslexia detection tool (ODEDYS-2; ¹¹² and the Alouette-R reading task ¹¹³).

596 For each of the word reading tasks (regular, irregular or pseudowords), participants had
597 to read as rapidly and accurately as possible a list of 20 words. Each task provided a *reading*
598 score computed as the number of words correctly read divided by the reading time (in seconds).

599 In the Alouette-R task,¹¹³ children had 3 minutes to read as rapidly and accurately as
600 possible a text of 256 words. This text is composed by a succession of words which do not tell

601 a meaningful story. This peculiarity forces children to solely rely on their reading skills and
602 prevents children from using anticipation or inference strategies that could boost the reading
603 scores. An *accuracy* score was computed as the number of words correctly read divided by the
604 total number of words read, and a *speed* score as the number of words correctly read multiplied
605 by the ratio of 180 s (maximal reading time) to the effective reading time.

606

607 ***Phonological processing***

608 The initial phoneme suppression and initial phonemes fusion tasks of the ODEDYS-2
609 ¹¹² was used to assess phonological processing.

610 In the initial phoneme suppression task, children had to repeat orally presented words
611 while intentionally suppressing the initial phoneme of the word (*i.e.* dog -> og). In total, 10
612 words were presented, and performance was quantified as percentage correct.

613 In the initial phoneme fusion task, children had to combine the initial phoneme of two
614 orally presented words to create a new (non-)word (*i.e.*, *Big & Owen* -> /bo/). In total, 10 pairs
615 of words were presented, and performance was quantified as percentage correct.

616

617 ***Rapid Automatized Naming***

618 We used the RAN task of the ODEDYS-2.¹¹² Children had to name as rapidly and
619 accurately as possible 25 pictures (5 different pictures randomly repeated 5 times).
620 Performance was quantified as the total time to complete the task, meaning that the lower the
621 score, the better the performance.

622

623 ***Phonological memory***

624 The forward and backward digit repetition task from the ODEDYS-2 ¹¹² was used to
625 assess phonological memory.

626 In the forward digit repetition task, children were asked to repeat orally presented
627 numbers series in the same order as presented. The series are different at every trial. The first
628 series contains 3 digits, and the size of the series is incremented by one every second trial. The
629 task ends after a failure to repeat the 2 series of a given size. Forward digit span score was
630 taken as the number of digits in the last correctly repeated series.

631 The backward digit repetition task is akin to the forward one. The only difference is
632 that digit series have to be repeated in the exact reverse order (e.g., children presented 1 2 3 4
633 have to repeat 4 3 2 1).

634

635 *Attention abilities*

636 The Bells test ¹¹⁴ was used to assess visual attention and the TAP auditory attention
637 subtest ¹¹⁵ to assess the auditory attentional level.

638 In the Bells test, children had 2 minutes to find as many bells as possible on a sheet
639 comprising 35 bells scattered among 280 visual distractors. Performance was quantified as the
640 number of bells found divided by the time needed.

641 In the TAP auditory attention subtest, a, children had to focus their attention during 3
642 min 20 s on an auditory stream. Children were hearing a train of 200 pure tone stimuli lasting
643 500 ms with a 1000-ms stimulus onset asynchrony. Tones alternated between high (1073 Hz)
644 and low (450 Hz) pitch. There were 16 occurrences in which 2 high or low pitch tones were
645 following one another. Only in this case, participants had to press a response button as fast as
646 possible. A performance score was quantified as the number of correct responses, a speed score
647 as the mean response time, and a failure score as the number of responses to tones differing in
648 pitch with the preceding one.

649

650 ***Non-verbal intelligence***

651 The brief version of the Weschler Nonverbal (WNV) Scale of Ability ¹¹⁶ was used to
652 assess non-verbal intelligence.

653 This assessment consisted of matrices and recognition subtests for children younger
654 than 8 years. Older children were assessed with matrices and spatial memory subtests.

655 In matrices subtest, children were presented with incomplete visual matrices and had to
656 select the good missing portion among 4 or 5 response options. The subtest ended when 4
657 mistakes were made in the last 5 trials. A raw score was taken as the number of correctly
658 completed matrices. This raw score was converted to a *T* score by comparison with values
659 provided in a table of norms.

660 In recognition subtest, children had to carefully look at visual geometric designs that
661 were presented one by one for three seconds. After each presentation, they had to identify the
662 previously seen design among four or five response options. The subtest ended when 4 mistakes
663 were made in the last 5 recognition trials. A raw score was taken as the number of correctly
664 recognized drawings. This raw score was converted to a *T* score by comparison with values
665 provided in a table of norms.

666 In spatial memory subtest, children were presented with a board with 10 cubes spread
667 on it, and were asked to mimic the examiner's tapping sequence. The sequences are different
668 on every trial. The first sequence consists in tapping on 2 cubes, and the size of the sequences
669 is incremented by one every second trial. The task ends after a failure to repeat 2 sequences of
670 a given size. This task was performed twice, in the forward and backward directions. For each
671 direction, a raw score was taken as the number of correctly repeated sequences. Raw scores
672 were summed and converted to a *T* score by comparison with values provided in a table of
673 norms.

674 Total non-verbal IQ was computed as the sum of both *T* scores, which compared to a
675 table of norms provided a *Total non-verbal IQ* score.

676

677 **Neuroimaging assessment**

678 ***Stimuli***

679 The stimuli were derived from 12 audiovisual recordings of 4 native French-speaking
680 actors (2 females, 3 recordings per actor) telling a story for ~6-min (mean \pm SD, 6.0 ± 0.8 min)
681 (see Supplementary Methods for details on recording of video stimuli). In each video, the first
682 5 s were kept unaltered to enable children to unambiguously identify the actor's voice and face
683 they were requested to attend to. The remainder of the video was divided into 10 consecutive
684 blocks of equal size that were assigned to 9 conditions. Two blocks were assigned to the
685 *noiseless* condition in which the audio track was kept but the video was replaced by static
686 pictures illustrating the story (mean \pm SD picture presentation time across all videos, $27.7 \pm$
687 10.8 s). The remaining 8 blocks were assigned to 8 conditions in which the original sound was
688 mixed with a background noise at 3 dB signal-to-noise ratio (SNR). There were 4 different
689 types of noise, and each type of noise was presented once with the original video, thereby
690 giving access to lip-read information (*lips* visual conditions), and once with the static pictures
691 illustrating the story (*pics* visual conditions). The different types of noise differed in the degree
692 of energetic and informational interference they introduced.⁵⁴ The non-energetic non-
693 informational noise was a white noise filtered through 100–10000-Hz. The (maximally-
694)energetic non-informational noise had its spectral properties dynamically adapted to mirror
695 those of the actor's voice ~1 s around (see Supplementary Methods for the procedure used to
696 build the energetic non-informational noise). The non-(or least-)energetic informational noise
697 was a 5-talker cocktail party noise recorded by individuals of gender opposite to the actor's
698 (i.e., a 5-man for female actors). The (maximally-)energetic informational noise was a 5-talker

699 cocktail party noise recorded by individuals of gender identical to the actor's. The assignment
700 of conditions to blocks was random, with the constraint that each of the 5 first and last blocks
701 contained exactly 1 *noiseless* audio, 2 *lips* videos, 2 energetic noises, and 2 informational
702 noises. Smooth audio and video transitions between blocks was ensured with 2-s fade-in and
703 fade-out. Ensuing videos were grouped in 3 disjoint sets featuring one video of each of the
704 actors (total set duration: 23.0, 24.3, 24.65 min), and there were 4 versions of each set differing
705 in condition random ordering.

706

707 ***Experimental paradigm***

708 During the imaging session, participants were laying on a bed with their head inside the
709 MEG helmet. Their brain activity was recorded while they were attending 4 videos (separate
710 recording for each video) of a randomly selected set and ordering of the videos presented in a
711 random order, and finally while they were at *rest* (eyes opened, fixation cross) for 5 min. They
712 were instructed to watch the videos attentively, listen to the actors' voice while ignoring the
713 interfering noise, and remain as still as possible. After each video, they were asked 10 yes/no
714 comprehension questions related to each of the 10 blocks/conditions (data not analyzed here).
715 Videos were projected onto a back-projection screen placed vertically, ~120 cm away from the
716 MEG helmet. The inner dimensions of the black frame were 35.2 cm (horizontal) and 28.8 cm
717 (vertical), and actors face spanned ~15 cm (horizontal) and ~20 cm (vertical). Participants
718 could see the screen through a mirror placed above their head. In total the optical path from the
719 screen to participants' eyes was of ~150 cm. Sounds were delivered at 60 dB (measured at ear-
720 level) through a MEG-compatible front-facing flat-panel loudspeaker (Panphonics Oy, Espoo,
721 Finland) placed ~1 m behind the screen.

722

723 ***Data acquisition***

724 During the experimental conditions, participants' brain activity was recorded with MEG
725 at the CUB Hôpital Erasme. Neuromagnetic signals were recorded with a whole-scalp-covering
726 MEG system (Triux, Elekta) placed in a lightweight magnetically shielded room (Maxshield,
727 Elekta), the characteristics of which being described elsewhere.¹¹⁷ The sensor array of the MEG
728 system comprised 306 sensors arranged in 102 triplets of one magnetometer and two
729 orthogonal planar gradiometers. Magnetometers measure the radial component of the magnetic
730 field, while planar gradiometers measure its spatial derivative in the tangential directions. MEG
731 signals were band-pass filtered at 0.1–330 Hz and sampled at 1000 Hz.

732 We used 4 head-position indicator coils to monitor subjects' head position during the
733 experimentation. Before the MEG session, we digitized the location of these coils and at least
734 300 head-surface points (on scalp, nose, and face) with respect to anatomical fiducials with an
735 electromagnetic tracker (Fastrack, Polhemus).

736 Finally, subjects' high-resolution 3D-T1 cerebral images were acquired with a magnetic
737 resonance imaging (MRI) scanner (MRI 1.5T, Intera, Philips) after the MEG session.

738

739 ***Data pre-processing***

740 Continuous MEG data were first preprocessed off-line using the temporal signal space
741 separation method implemented in MaxFilter software (MaxFilter, Neuromag, Elekta;
742 correlation limit 0.9, segment length 20 s) to suppress external interferences and to correct for
743 head movements.^{118,119} To further suppress physiological artifacts, 30 independent components
744 were evaluated from the data band-pass filtered at 0.1–25 Hz and reduced to a rank of 30 with
745 principal component analysis. Independent components corresponding to heartbeat, eye-blink,
746 and eye-movement artifacts were identified, and corresponding MEG signals reconstructed by
747 means of the mixing matrix were subtracted from the full-rank data. Across subjects and

748 conditions, the number of subtracted components was 3.45 ± 1.23 (mean \pm SD across subjects
749 and recordings). Finally, a window time of 1 s time points at timings 1 s around remaining
750 artifacts were set to bad. Data were considered contaminated by artifacts when MEG amplitude
751 exceeded 5 pT in at least one magnetometer or 1 pT/cm in at least one gradiometer.

752 We extracted the temporal envelope of the attended speech (actors' voice) using the
753 optimal approach proposed by Biesmans et al.¹²⁰. Briefly, audio signals were bandpass filtered
754 using a gammatone filter bank (15 filters centered on logarithmically-spaced frequencies from
755 150 Hz to 4000 Hz), and subband envelopes were computed using Hilbert transform, elevated
756 to the power 0.6, and averaged across bands.

757

758 *Accuracy of speech envelope reconstruction and normalized CTS*

759 For each condition and participant, a global value of cortical tracking of the attended
760 speech was evaluated for all left-hemisphere sensors at once, and for all right-hemisphere
761 sensors at once. Using the mTRF toolbox,⁵⁸ we trained a decoder on MEG data to reconstruct
762 speech temporal envelope, and estimated its Pearson correlation with real speech temporal
763 envelope. This correlation is often referred to as the reconstruction accuracy, and it provides a
764 global measure of cortical tracking of speech. See Supplementary Methods for a full description
765 of the procedure and statistical assessment. A similar approach has been used in previous
766 studies on the cortical tracking of speech.^{47,51,60,61}

767 Based on CTS values in noiseless condition ($CTS_{\text{noiseless}}$) and in each SiN condition
768 (CTS_{SiN}), we estimated nCTS as follows:

$$769 \quad nCTS = (CTS_{\text{SiN}} - CTS_{\text{noiseless}}) / (CTS_{\text{SiN}} + CTS_{\text{noiseless}}).$$

770 This index can however be misleading when derived from negative CTS values (which may
771 happen since CTS is an unsquared correlation values). For this reason, and for the sake of nCTS

772 computation only, CTS values below a threshold of 10% of the mean CTS across all subjects,
773 conditions and hemispheres were set to that threshold prior to nCTS computation.

774

775 **Linear mixed-effects modeling of nCTS and reading values**

776 All behavioral and nCTS measures were corrected for IQ, age, time spent at elementary
777 school, and for outliers (see Supplementary Methods for details on this procedure).

778 We performed linear mixed-effects analysis with R ¹²¹ and *lme4* ¹²² to identify how
779 different fixed effects modulate nCTS. We started with a null model that included only a
780 different random intercept for each subject. The model was iteratively compared to models
781 incremented with simple fixed effects of *hemisphere*, *noise* (non-energetic non-informational,
782 energetic non-informational, non-energetic informational, and energetic informational), and
783 *visual* (*lips* vs. *pics*) added one by one. At every step, the most significant fixed effect was
784 retained, until the addition of the remaining effects did not improve the model any further ($p >$
785 0.05). The same procedure was then repeated to refine the ensuing model with the interactions
786 of the simple fixed effects of order 2 (e.g., *hemisphere* \times *noise*) and then 3 (*hemisphere* \times *noise*
787 \times *visual*).

788 We followed the same approach to identify how reading abilities (5 standardized
789 scores) relate to classical behavioral predictors of reading and features of nCTS. In that
790 analysis, we first considered a non-zero slope for the classical behavioral predictors identical
791 for all reading scores, then a non-zero slope for the classical behavioral predictors different for
792 all reading scores, then a non-zero slope for the features of nCTS identical for all reading
793 scores, and finally a non-zero slope for the features of nCTS different for all reading scores.

794

795 **Partial information decomposition**

796 We used PID to appraise without *a priori* the relation between reading abilities, cortical
797 measures of SiN processing, and classical behavioral predictors of reading. In general, PID
798 decomposes the mutual information (MI) quantifying the relationship between two explanatory
799 variables (or sets of explanatory variables) and a single target, into four constituent terms: the
800 unique information about the target which is available separately from each explanatory
801 variable alone, the redundant or shared information which is common to the two explanatory
802 variables, and synergistic information, which is information about the target that is available
803 only when both explanatory variables are observed together (e.g. the relationship between their
804 values is informative about the target).^{62–64} In our analysis, the 5 reading scores were used as
805 the target, the features nCTS as the first set of explanatory variables, and behavioral scores as
806 the second set of explanatory variables. PID was also used to better understand the nature of
807 some other statistical associations we uncovered. See Supplementary Methods for further
808 details on PID and its statistical assessment.

809 **Data availability**

810 The data and the code that support the findings of this study are available at “a link to
811 a OSF repository will be provided upon positive review”.

5. References

1. Leppänen, P. H. T. *et al.* Infant brain responses associated with reading-related skills before school and at school age. *Neurophysiol. Clin.* **42**, 35–41 (2012).
2. Share, D. L., Jorm, A. F., Maclean, R. & Matthews, R. Sources of individual differences in reading acquisition. *Journal of Educational Psychology* vol. 76 1309–1324 (1984).
3. Caravolas, M., Hulme, C. & Snowling, M. J. The Foundations of Spelling Ability: Evidence from a 3-Year Longitudinal Study. *Journal of Memory and Language* vol. 45 751–774 (2001).
4. Muter, V. & Snowling, M. Concurrent and Longitudinal Predictors of Reading: The Role of Metalinguistic and Short-Term Memory Skills. *Reading Research Quarterly* vol. 33 320–337 (1998).
5. Gathercole, S. E. & Baddeley, A. D. Phonological working memory: A critical building block for reading development and vocabulary acquisition? *European Journal of Psychology of Education* vol. 8 259–272 (1993).
6. Manis, F. R., Doi, L. M. & Bhadha, B. Naming speed, phonological awareness, and orthographic knowledge in second graders. *J. Learn. Disabil.* **33**, 325–33, 374 (2000).
7. Wimmer, H., Mayringer, H. & Landerl, K. The double-deficit hypothesis and difficulties in learning to read a regular orthography. *Journal of Educational Psychology* vol. 92 668–680 (2000).
8. Wimmer, H., Mayringer, H. & Landerl, K. Poor Reading: A Deficit in Skill-Automatization or a Phonological Deficit? *Scientific Studies of Reading* vol. 2 321–340 (1998).
9. Samuelsson, S. & Lundberg, I. The impact of environmental factors on components of reading and dyslexia. *Annals of Dyslexia* vol. 53 201–217 (2003).
10. Hooper, S. R., Roberts, J., Sideris, J., Burchinal, M. & Zeisel, S. Longitudinal predictors of reading and math trajectories through middle school for African American versus Caucasian students across two samples. *Dev. Psychol.* **46**, 1018–1029 (2010).
11. Klatte, M., Bergström, K. & Lachmann, T. Does noise affect learning? A short review on noise effects on cognitive performance in children. *Frontiers in Psychology* vol. 4 (2013).
12. Stockman, J. A. Aircraft and Road Traffic Noise and Children’s Cognition and Health: A Cross-

- National Study. *Yearbook of Pediatrics* vol. 2007 69–71 (2007).
13. McDermott, J. H. The cocktail party problem. *Current Biology* vol. 19 R1024–R1027 (2009).
 14. Anderson, S. & Kraus, N. Sensory-cognitive interaction in the neural encoding of speech in noise: a review. *J. Am. Acad. Audiol.* **21**, 575–585 (2010).
 15. White-Schwoch, T. *et al.* Auditory Processing in Noise: A Preschool Biomarker for Literacy. *PLoS Biol.* **13**, e1002196 (2015).
 16. Calcus, A., Colin, C., Deltenre, P. & Kolinsky, R. Informational masking of speech in dyslexic children. *The Journal of the Acoustical Society of America* vol. 137 EL496–EL502 (2015).
 17. Ziegler, J. C., Pech-Georgel, C., George, F. & Lorenzi, C. Speech-perception-in-noise deficits in dyslexia. *Developmental Science* vol. 12 732–745 (2009).
 18. Dole, M., Hoen, M. & Meunier, F. Speech-in-noise perception deficit in adults with dyslexia: Effects of background type and listening configuration. *Neuropsychologia* vol. 50 1543–1552 (2012).
 19. Nittrouer, S. From Ear to Cortex: A Perspective on What Clinicians Need to Understand About Speech Perception and Language Processing. *Lang. Speech Hear. Serv. Sch.* **33**, 237–252 (2002).
 20. Fallon, M., Trehub, S. E. & Schneider, B. A. Children’s perception of speech in multitalker babble. *The Journal of the Acoustical Society of America* vol. 108 3023–3029 (2000).
 21. Lewis, D., Hoover, B., Choi, S. & Stelmachowicz, P. Relationship between speech perception in noise and phonological awareness skills for children with normal hearing. *Ear Hear.* **31**, 761–768 (2010).
 22. Coltheart, M., Rastle, K., Perry, C., Langdon, R. & Ziegler, J. DRC: a dual route cascaded model of visual word recognition and reading aloud. *Psychol. Rev.* **108**, 204–256 (2001).
 23. Coltheart, M., Curtis, B., Atkins, P. & Haller, M. Models of reading aloud: Dual-route and parallel-distributed-processing approaches. *Psychological Review* vol. 100 589–608 (1993).
 24. Fiez, J. A. & Petersen, S. E. Neuroimaging studies of word reading. *Proceedings of the National Academy of Sciences* **95**, 914–921 (1998).
 25. Turkeltaub, P. E., Eden, G. F., Jones, K. M. & Zeffiro, T. A. Meta-analysis of the functional neuroanatomy of single-word reading: method and validation. *Neuroimage* **16**, 765–780 (2002).
 26. McCandliss, B. D., Cohen, L. & Dehaene, S. The visual word form area: expertise for reading in the

- fusiform gyrus. *Trends Cogn. Sci.* **7**, 293–299 (2003).
27. Dehaene, S. & Cohen, L. The unique role of the visual word form area in reading. *Trends Cogn. Sci.* **15**, 254–262 (2011).
 28. Destoky, F. *et al.* Comparing the potential of MEG and EEG to uncover brain tracking of speech temporal envelope. *Neuroimage* **184**, 201–213 (2019).
 29. Vander Ghinst, M. *et al.* Cortical Tracking of Speech-in-Noise Develops from Childhood to Adulthood. *J. Neurosci.* **39**, 2938–2950 (2019).
 30. Bourguignon, M. *et al.* The pace of prosodic phrasing couples the listener’s cortex to the reader's voice. *Human Brain Mapping* vol. 34 314–326 (2013).
 31. Ahissar, E. *et al.* Speech comprehension is correlated with temporal response patterns recorded from auditory cortex. *Proc. Natl. Acad. Sci. U. S. A.* **98**, 13367–13372 (2001).
 32. Gross, J. *et al.* Speech rhythms and multiplexed oscillatory sensory coding in the human brain. *PLoS Biol.* **11**, e1001752 (2013).
 33. Luo, H. & Poeppel, D. Phase patterns of neuronal responses reliably discriminate speech in human auditory cortex. *Neuron* **54**, 1001–1010 (2007).
 34. Molinaro, N., Lizarazu, M., Lallier, M., Bourguignon, M. & Carreiras, M. Out-of-synchrony speech entrainment in developmental dyslexia. *Hum. Brain Mapp.* **37**, 2767–2783 (2016).
 35. Peelle, J. E., Gross, J. & Davis, M. H. Phase-locked responses to speech in human auditory cortex are enhanced during comprehension. *Cereb. Cortex* **23**, 1378–1387 (2013).
 36. Meyer, L. & Gumbert, M. Synchronization of Electrophysiological Responses with Speech Benefits Syntactic Information Processing. *J. Cogn. Neurosci.* **30**, 1066–1074 (2018).
 37. Meyer, L., Henry, M. J., Gaston, P., Schmuck, N. & Friederici, A. D. Linguistic Bias Modulates Interpretation of Speech via Neural Delta-Band Oscillations. *Cereb. Cortex* **27**, 4293–4302 (2017).
 38. Vander Ghinst, M. *et al.* Left Superior Temporal Gyrus Is Coupled to Attended Speech in a Cocktail-Party Auditory Scene. *J. Neurosci.* **36**, 1596–1606 (2016).
 39. Ding, N., Melloni, L., Zhang, H., Tian, X. & Poeppel, D. Cortical tracking of hierarchical linguistic structures in connected speech. *Nat. Neurosci.* **19**, 158–164 (2016).
 40. Riecke, L., Formisano, E., Sorger, B., Başkent, D. & Gaudrain, E. Neural Entrainment to Speech

- Modulates Speech Intelligibility. *Curr. Biol.* **28**, 161–169.e5 (2018).
41. Vanthornhout, J., Decruy, L., Wouters, J., Simon, J. Z. & Francart, T. Speech intelligibility predicted from neural entrainment of the speech envelope. *Journal of the Association for Research in Otolaryngology* (2018) doi:10.1101/246660.
 42. Ding, N. & Simon, J. Z. Cortical entrainment to continuous speech: functional roles and interpretations. *Front. Hum. Neurosci.* **8**, 311 (2014).
 43. Fuglsang, S. A., Dau, T. & Hjortkjær, J. Noise-robust cortical tracking of attended speech in real-world acoustic scenes. *Neuroimage* **156**, 435–444 (2017).
 44. Puschmann, S. *et al.* The Right Temporoparietal Junction Supports Speech Tracking During Selective Listening: Evidence from Concurrent EEG-fMRI. *J. Neurosci.* **37**, 11505–11516 (2017).
 45. Rimmele, J. M., Golumbic, E. Z., Schröger, E. & Poeppel, D. The effects of selective attention and speech acoustics on neural speech-tracking in a multi-talker scene. *Cortex* vol. 68 144–154 (2015).
 46. Broderick, M. P., Anderson, A. J., Di Liberto, G. M., Crosse, M. J. & Lalor, E. C. Electrophysiological Correlates of Semantic Dissimilarity Reflect the Comprehension of Natural, Narrative Speech. *Curr. Biol.* **28**, 803–809.e3 (2018).
 47. Ding, N. & Simon, J. Z. Emergence of neural encoding of auditory objects while listening to competing speakers. *Proc. Natl. Acad. Sci. U. S. A.* **109**, 11854–11859 (2012).
 48. Ding, N. & Simon, J. Z. Adaptive temporal encoding leads to a background-insensitive cortical representation of speech. *J. Neurosci.* **33**, 5728–5735 (2013).
 49. Horton, C., D’Zmura, M. & Srinivasan, R. Suppression of competing speech through entrainment of cortical oscillations. *J. Neurophysiol.* **109**, 3082–3093 (2013).
 50. Mesgarani, N. & Chang, E. F. Selective cortical representation of attended speaker in multi-talker speech perception. *Nature* **485**, 233–236 (2012).
 51. O’Sullivan, J. A. *et al.* Attentional Selection in a Cocktail Party Environment Can Be Decoded from Single-Trial EEG. *Cereb. Cortex* **25**, 1697–1706 (2014).
 52. Simon, J. Z. The encoding of auditory objects in auditory cortex: insights from magnetoencephalography. *Int. J. Psychophysiol.* **95**, 184–190 (2015).
 53. Zion-Golumbic, E. & Schroeder, C. E. Attention modulates ‘speech-tracking’ at a cocktail party.

- Trends in Cognitive Sciences* vol. 16 363–364 (2012).
54. Pollack, I. Auditory informational masking. *The Journal of the Acoustical Society of America* vol. 57 S5–S5 (1975).
 55. Sumbly, W. H. & Pollack, I. Visual Contribution to Speech Intelligibility in Noise. *The Journal of the Acoustical Society of America* vol. 26 212–215 (1954).
 56. Schwartz, J.-L., Berthommier, F. & Savariaux, C. Seeing to hear better: evidence for early audio-visual interactions in speech identification. *Cognition* **93**, B69–78 (2004).
 57. Goswami, U. Sensory theories of developmental dyslexia: three challenges for research. *Nat. Rev. Neurosci.* **16**, 43–54 (2015).
 58. Crosse, M. J., Di Liberto, G. M., Bednar, A. & Lalor, E. C. The Multivariate Temporal Response Function (mTRF) Toolbox: A MATLAB Toolbox for Relating Neural Signals to Continuous Stimuli. *Front. Hum. Neurosci.* **10**, 604 (2016).
 59. Bourguignon, M., Baart, M., Kapnoula, E. C. & Molinaro, N. Lip-reading enables the brain to synthesize auditory features of unknown silent speech. *J. Neurosci.* (2019)
doi:10.1523/JNEUROSCI.1101-19.2019.
 60. Zion-Golumbic, E. M. *et al.* Mechanisms underlying selective neuronal tracking of attended speech at a ‘cocktail party’. *Neuron* **77**, 980–991 (2013).
 61. Lalor, E. C. & Foxe, J. J. Neural responses to uninterrupted natural speech can be extracted with precise temporal resolution. *Eur. J. Neurosci.* **31**, 189–193 (2010).
 62. Daube, C., Ince, R. A. A. & Gross, J. Simple Acoustic Features Can Explain Phoneme-Based Predictions of Cortical Responses to Speech. *Curr. Biol.* **29**, 1924–1937.e9 (2019).
 63. Ince, R. Measuring Multivariate Redundant Information with Pointwise Common Change in Surprisal. *Entropy* vol. 19 318 (2017).
 64. Ince, R. A. A. *et al.* A statistical framework for neuroimaging data analysis based on mutual information estimated via a gaussian copula. *Human Brain Mapping* **38**, 1541–1573 (2017).
 65. Molinaro, N. & Lizarazu, M. Delta(but not theta)-band cortical entrainment involves speech-specific processing. *European Journal of Neuroscience* vol. 48 2642–2650 (2018).
 66. Allport, D. A. & Funnell, E. Components of the Mental Lexicon. *Philosophical Transactions of the*

- Royal Society B: Biological Sciences* vol. 295 397–410 (1981).
67. McClelland, J. L. & Rogers, T. T. The parallel distributed processing approach to semantic cognition. *Nat. Rev. Neurosci.* **4**, 310–322 (2003).
 68. Ramus, F. The neural basis of reading acquisition. in *The Cognitive Neurosciences (3rd ed.)* (ed. Gazzaniga, M. S.) 815–824 (2004).
 69. Ricketts, J., Davies, R., Masterson, J., Stuart, M. & Duff, F. J. Evidence for semantic involvement in regular and exception word reading in emergent readers of English. *J. Exp. Child Psychol.* **150**, 330–345 (2016).
 70. Kaandorp, M. W., De Groot, A. M. B., Festen, J. M., Smits, C. & Goverts, S. T. The influence of lexical-access ability and vocabulary knowledge on measures of speech recognition in noise. *Int. J. Audiol.* **55**, 157–167 (2016).
 71. Carroll, R., Warzybok, A., Kollmeier, B. & Ruigendijk, E. Age-Related Differences in Lexical Access Relate to Speech Recognition in Noise. *Front. Psychol.* **7**, 990 (2016).
 72. Golombic, E. Z., Zion Golombic, E., Cogan, G. B., Schroeder, C. E. & Poeppel, D. Visual Input Enhances Selective Speech Envelope Tracking in Auditory Cortex at a ‘Cocktail Party’. *Journal of Neuroscience* vol. 33 1417–1426 (2013).
 73. Park, H., Ince, R. A. A., Schyns, P. G., Thut, G. & Gross, J. Representational interactions during audiovisual speech entrainment: Redundancy in left posterior superior temporal gyrus and synergy in left motor cortex. *PLoS Biol.* **16**, e2006558 (2018).
 74. Park, H., Kayser, C., Thut, G. & Gross, J. Lip movements entrain the observers’ low-frequency brain oscillations to facilitate speech intelligibility. *eLife* vol. 5 (2016).
 75. Bourguignon, M., Baart, M., Kapnoula, E. C. & Molinaro, N. Hearing through lip-reading: the brain synthesizes features of absent speech. doi:10.1101/395483.
 76. Giordano, B. L. *et al.* Contributions of local speech encoding and functional connectivity to audiovisual speech perception. *eLife* vol. 6 (2017).
 77. MacLeod, A. & Summerfield, Q. Quantifying the contribution of vision to speech perception in noise. *Br. J. Audiol.* **21**, 131–141 (1987).
 78. Helfer, K. S. & Freyman, R. L. The role of visual speech cues in reducing energetic and

- informational masking. *J. Acoust. Soc. Am.* **117**, 842–849 (2005).
79. Crosse, M. J., Di Liberto, G. M. & Lalor, E. C. Eye Can Hear Clearly Now: Inverse Effectiveness in Natural Audiovisual Speech Processing Relies on Long-Term Crossmodal Temporal Integration. *J. Neurosci.* **36**, 9888–9895 (2016).
80. Hauswald, A., Lithari, C., Collignon, O., Leonardelli, E. & Weisz, N. A Visual Cortical Network for Deriving Phonological Information from Intelligible Lip Movements. *Curr. Biol.* **28**, 1453–1459.e3 (2018).
81. O’Sullivan, A. E., Crosse, M. J., Di Liberto, G. M. & Lalor, E. C. Visual Cortical Entrainment to Motion and Categorical Speech Features during Silent Lipreading. *Front. Hum. Neurosci.* **10**, 679 (2016).
82. Crosse, M. J. & Lalor, E. C. The cortical representation of the speech envelope is earlier for audiovisual speech than audio speech. *J. Neurophysiol.* **111**, 1400–1408 (2014).
83. Baart, M., de Boer-Schellekens, L. & Vroomen, J. Lipread-induced phonetic recalibration in dyslexia. *Acta Psychol.* **140**, 91–95 (2012).
84. Keetels, M., Bonte, M. & Vroomen, J. A Selective Deficit in Phonetic Recalibration by Text in Developmental Dyslexia. *Front. Psychol.* **9**, 710 (2018).
85. van Laarhoven, T., Keetels, M., Schakel, L. & Vroomen, J. Audio-visual speech in noise perception in dyslexia. *Developmental Science* vol. 21 e12504 (2018).
86. Bastien-Toniazzo, M., Stroumza, A. & Cavé, C. Audio-visual perception and integration in developmental dyslexia: An exploratory study using the McGurk effect. *Curr. Psychol. Lett.* **25**, (2010).
87. Rüsseler, J., Gerth, I., Heldmann, M. & Münte, T. F. Audiovisual perception of natural speech is impaired in adult dyslexics: an ERP study. *Neuroscience* **287**, 55–65 (2015).
88. Ramirez, J. & Mann, V. Using auditory-visual speech to probe the basis of noise-impaired consonant-vowel perception in dyslexia and auditory neuropathy. *J. Acoust. Soc. Am.* **118**, 1122–1133 (2005).
89. Campbell, R. The processing of audio-visual speech: empirical and neural bases. *Philos. Trans. R. Soc. Lond. B Biol. Sci.* **363**, 1001–1010 (2008).

90. van Atteveldt, N., Formisano, E., Goebel, R. & Blomert, L. Integration of Letters and Speech Sounds in the Human Brain. *Neuron* vol. 43 271–282 (2004).
91. Raij, T., Uutela, K. & Hari, R. Audiovisual Integration of Letters in the Human Brain. *Neuron* vol. 28 617–625 (2000).
92. Blomert, L. The neural signature of orthographic–phonological binding in successful and failing reading development. *NeuroImage* vol. 57 695–703 (2011).
93. Bernstein, L. E. & Liebenthal, E. Neural pathways for visual speech perception. *Frontiers in Neuroscience* vol. 8 (2014).
94. Leybaert, J. *et al.* Atypical audio-visual speech perception and McGurk effects in children with specific language impairment. *Front. Psychol.* **5**, 422 (2014).
95. Hood, M. & Conlon, E. Visual and auditory temporal processing and early reading development. *Dyslexia* **10**, 234–252 (2004).
96. Boets, B., Wouters, J., van Wieringen, A., De Smedt, B. & Ghesquière, P. Modelling relations between sensory processing, speech perception, orthographic and phonological ability, and literacy achievement. *Brain Lang.* **106**, 29–40 (2008).
97. Katz, R. B., Healy, A. F. & Shankweiler, D. Phonetic coding and order memory in relation to reading proficiency: A comparison of short-term memory for temporal and spatial order information. *Applied Psycholinguistics* vol. 4 229–250 (1983).
98. Shankweiler, D. The speech code and learning to read. *Journal of Experimental Psychology: Human Learning & Memory* vol. 5 531–545 (1979).
99. Brady, S., Shankweiler, D. & Mann, V. Speech perception and memory coding in relation to reading ability. *J. Exp. Child Psychol.* **35**, 345–367 (1983).
100. Araújo, S., Reis, A., Petersson, K. M. & Faisca, L. Rapid automatized naming and reading performance: A meta-analysis. *Journal of Educational Psychology* vol. 107 868–883 (2015).
101. Lervåg, A. & Hulme, C. Rapid automatized naming (RAN) taps a mechanism that places constraints on the development of early reading fluency. *Psychol. Sci.* **20**, 1040–1048 (2009).
102. Norton, E. S. & Wolf, M. Rapid automatized naming (RAN) and reading fluency: implications for understanding and treatment of reading disabilities. *Annu. Rev. Psychol.* **63**, 427–452 (2012).

103. Georgiou, G. K., Parrila, R., Cui, Y. & Papadopoulos, T. C. Why is rapid automatized naming related to reading? *J. Exp. Child Psychol.* **115**, 218–225 (2013).
104. Landerl, K. *et al.* Phonological Awareness and Rapid Automatized Naming as Longitudinal Predictors of Reading in Five Alphabetic Orthographies with Varying Degrees of Consistency. *Scientific Studies of Reading* vol. 23 220–234 (2019).
105. Torgesen, J. K., Wagner, R. K., Rashotte, C. A., Burgess, S. & Hecht, S. Contributions of Phonological Awareness and Rapid Automatic Naming Ability to the Growth of Word-Reading Skills in Second-to Fifth-Grade Children. *Scientific Studies of Reading* vol. 1 161–185 (1997).
106. Sprenger-Charolles, L., Siegel, L. S., Béchennec, D. & Serniclaes, W. Development of phonological and orthographic processing in reading aloud, in silent reading, and in spelling: a four-year longitudinal study. *J. Exp. Child Psychol.* **84**, 194–217 (2003).
107. Elhassan, Z., Crewther, S. G. & Bavin, E. L. The Contribution of Phonological Awareness to Reading Fluency and Its Individual Sub-skills in Readers Aged 9- to 12-years. *Front. Psychol.* **8**, 533 (2017).
108. Boets, B. *et al.* Intact but less accessible phonetic representations in adults with dyslexia. *Science* **342**, 1251–1254 (2013).
109. Perfetti, C. A., Beck, I., Bell, L. C. & Hughes, C. Phonemic Knowledge and Learning to Read are Reciprocal: A Longitudinal Study of First Grade Children. *Merrill. Palmer. Q.* **33**, 283–319 (1987).
110. Demanez L, Dony-Closon B, Lhonneux-Ledoux E, Demanez JP. Central auditory processing assessment: a French-speaking battery. *Acta Otorhinolaryngol. Belg.* **57**, 275–290 (2003).
111. Currie, C. E., Elton, R. A., Todd, J. & Platt, S. Indicators of socioeconomic status for adolescents: the WHO Health Behaviour in School-aged Children Survey. *Health Educ. Res.* **12**, 385–397 (1997).
112. Jacquier-Roux, M., Valdois, S. & Zorman, M. *Odédys: outil de dépistage des dyslexies.* (2005).
113. Lefavrais, P. *Manuel du test de l'alouette.* (2005).
114. Gauthier, L., Dehaut, F. & Joanette, Y. Bells Test. *PsycTESTS Dataset* (1989) doi:10.1037/t28075-000.
115. Fimm, B. & Zimmermann, P. A test battery for attentional performance. in *Applied Neuropsychology of Attention. Theory, Diagnosis and Rehabilitation* 110–151 (2002).

116. Wechsler, D. & Naglieri, J. A. *WNV: Wechsler Nonverbal Scale of Ability ; Administration and Scoring Manual*. (2006).
117. De Tiège, X. *et al.* Recording epileptic activity with MEG in a light-weight magnetic shield. *Epilepsy Res.* **82**, 227–231 (2008).
118. Taulu, S. & Simola, J. Spatiotemporal signal space separation method for rejecting nearby interference in MEG measurements. *Phys. Med. Biol.* **51**, 1759–1768 (2006).
119. Taulu, S., Simola, J. & Kajola, M. Applications of the signal space separation method. *IEEE Trans. Signal Process.* **53**, 3359–3372 (2005).
120. Biesmans, W., Das, N., Francart, T. & Bertrand, A. Auditory-Inspired Speech Envelope Extraction Methods for Improved EEG-Based Auditory Attention Detection in a Cocktail Party Scenario. *IEEE Trans. Neural Syst. Rehabil. Eng.* **25**, 402–412 (2017).
121. R Core Team. *R: A language and environment for statistical computing*. vol. 3 (R Foundation for Statistical Computing, Vienna, Austria, 2018).
122. Bates, D. M., Maechler, M. & Bolker, B. *lme4: Linear mixed-effects models using Eigen and Eigen++*. (2011).

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Supplementary Material

Supplementary methods

Recording of video stimuli

The 12 video stimuli of actors telling a story were recorded with a digital camera (Sony handycam, HDR-CX115E). Audio signals were recorded with both the internal microphone of the camera, and an independent high quality microphone (Sony linear PCM recorder, PCM-D50). Audio tracks were synchronized, and only the high-quality audio was kept. Video recordings were framed as a head-shots, and recorded at 50 frames per second (videos were 1920×1080 pixels in size, 24 bits/pixel, with an auditory sampling rate of 44100 Hz). The camera was placed ~ 1 m away from the actors, and the face spanned about half of the vertical field of view. Final images were resized to a resolution of 1152×864 pixels. A black old-style-TV-monitor frame was then added to the image.

Building the energetic non-informational noise

The (maximally-)energetic non-informational noise was derived from the actual actors' audio recording by i) Fourier transforming the sound in 2-s-long windows sliding by step of 0.5 s, ii) replacing the phase by random numbers, iii) inverse Fourier transforming the Fourier coefficients in each window, iv) multiplying these phase-shuffled sound segments by a sine window (i.e., half a sine cycle with 0 at edges, and 1 in the middle), and v) summing the contribution of each overlapping window. As a result, the spectral properties of this noise dynamically changed on a ~ 0.5 -s time scale to mirror those of the actor's voice ~ 1 s around.

Accuracy of speech envelope reconstruction

For each condition and participant, a global value of cortical tracking of the attended speech was evaluated for all left-hemisphere sensors at once, and for all right-hemisphere sensors at once.

The decoder tested on a given condition was built based on MEG data from all the other conditions. This procedure was preferred over a more conventional cross-validation approach in which the decoder is trained and tested on separate chunks of data from the same condition because of the paucity of data (*i.e.*, at most ~2.4 min of data per condition). It is based on the rationale that the different conditions do modulate response amplitude but not its topography and temporal dynamics. In practice, electrophysiological data were band-pass filtered at 0.2–1.5 Hz (phrasal rate) or 2–8 Hz (syllabic rate), resampled to 10 Hz (phrasal) or 40 Hz (syllabic) and standardized. The decoder was built based on MEG data from –500 ms to 1000 ms (phrasal) or from 0 ms to 250 ms (syllabic) with respect to speech temporal envelope. Filtering and delay ranges were as in previous studies for phrasal,^{28,59} and syllabic CTS.^{47,51,60,61} Regularization was applied to limit the norm of the derivative of the reconstructed speech temporal envelope,⁵⁸ by estimating the decoder for a fixed set of ridge values ($\lambda = 2^{-10}, 2^{-8}, 2^{-6}, 2^{-4}, 2^{-2}, 2^0$). The regularization parameter was determined with a classical 10-fold cross-validation approach: the data is split into 10 segments of equal length, the decoder is estimated for 9 segments and tested on the remaining segment, and this procedure is repeated 10 times until all segments have served as test segment. The ridge value yielding the maximum mean RA is then retained. The ensuing decoder was then used to reconstruct speech temporal envelope in the left-out condition. RA was then estimated in 10 disjoint consecutive segments. We then retained the mean of this RA, leaving us with one value for all combinations of subjects, conditions, hemispheres, and frequencies of interest.

Significance of RA in each participant, condition, hemisphere and frequency range was assessed with a *t*-test on the RA values evaluated on 10 disjoint segments.

Preprocessing of brain and behavioral indices

All behavioral and nCTS measures were corrected for IQ, age, and time spent at elementary school, and for outliers. For simplicity, we refer to the standardized IQ, age, and time spent at elementary school as the regressors.

An iterative procedure was used to simultaneously control for regressors and deal with outliers. First regressors were regressed out of each measure with an amount of regularization equal to 0.1% the maximal eigenvalue of the regressors' covariance matrix. Then measures deviating by more than 3 standard deviations from the mean were removed from the distribution. This procedure was repeated until there were no more outliers. Discarded data points were then set to the mean plus or minus 3 standard deviations.

Extraction of the relevant features of nCTS

In total, we derived 8 features of nCTS in SiN conditions based on the significant effects of hemisphere and conditions highlighted in Table 3 and Figure 2. There were 4 features for phrasal nCTS: (i) the mean nCTS (the mean standardized nCTS across conditions), (ii) the informational modulation in nCTS (the difference in standardized *nCTS* between informational and non-informational noise conditions averaged across all other factors), (iii) the visual modulation in *nCTS* (the difference in standardized nCTS between *lips* and *pics* visual conditions averaged across all informational noise conditions), and (iv) the hemispheric difference in nCTS (the contrast in standardized nCTS between *left* and *right* hemispheres averaged across all informational noise conditions). The same 4 features were used for syllabic nCTS except that visual and hemispheric modulations were evaluated based on averages across all other factors (and not just across informational noise conditions since visual and hemispheric modulations were seen in all noise conditions for syllabic CTS).

Partial information decomposition

PID was previously used to decompose the information brought by acoustic and visual speech signals about brain oscillatory activity,⁷³ and to compare auditory encoding models of MEG during speech processing.⁶² As in these references, we measure redundancy with pointwise common change in surprisal for Gaussian variables.⁶³ Continuous data values were first subject to a rank-normalisation (copula-normalised)⁶⁴ before being treated as Gaussian variables. A crucial advantage of this redundancy measure as opposed to other PID implementations is that it measures the overlapping information content at the pointwise level and therefore can be interpreted as a within sample (here participant) measure of redundant prediction, directly linked to the coding interpretations of MI. An advantage of the PID over variance partitioning approaches is that unique variance explained might, like conditional mutual information, be confounded by synergistic effects,¹²³ whereas PID with common change in surprisal gives the true unique contribution. While the PID has so far been applied within subject to trial data, information theoretic quantities can also be applied as a second level analysis, where each participant is a sample.¹²⁴

The statistical significance of the different information values was assessed with a nonparametric permutation test.¹²⁵ A permutation distribution was computed for each information value by randomly shuffling (10,000 times) children's target values, and a significance level was computed as the proportion values from the permutation distribution exceeding the observed value.

Supplementary results

Side measures are redundant with RAN and digit span but not with modulations in phrasal nCTS

The information about reading brought by the 3 “side” measures (visual modulation in syllabic nCTS, phoneme suppression and phoneme fusion) was redundant with that brought by a subset (possibly all) of the 4 “main” measures (RAN, phonological memory, visual and

informational modulation in phrasal nCTS). To identify this subset, we relied on the PID framework. In this analysis, PID assessed the nature of the information about reading abilities (target) brought by the 3 side measures (first set of explanatory variables) and the 4 main measures (second set of explanatory variables). Specifically, we considered as second set of explanatory variables all possible combinations of the 4 main measures (with or without RAN, with or without forward digit span, with or without the informational modulation in phrasal nCTS, and with or without the visual modulation in phrasal nCTS). Also, the analysis was run separately for the modulation in syllabic nCTS, and for both measures of phonological awareness (phoneme suppression and phoneme fusion) at once. Overall, the results tended to show that the visual modulation in syllabic nCTS provided unique information about reading only with regard to the two phrasal nCTS modulations (see Fig. S1A), and synergic information mainly with the two classical behavioral predictors of reading (see Fig. S1B). Noticeably, the level of synergic information about reading brought by the visual modulation in syllabic nCTS and either or both classical behavioral predictors of reading was not influenced by the addition of either or both of the two phrasal nCTS modulations. Similar results were obtained for the two measures of phonological awareness (see Fig. S1C & D).

Supplementary discussion

Limitations

We did not manipulate the SNR in SiN conditions in the present study. Instead, it was set to 3 dB so that the attended speech was always louder than the noise. Still, one could expect that large effect sizes would be uncovered in more challenging/discriminating listening conditions, as often encountered in classrooms.¹²⁶ However, children's SiN perception abilities are lower than adults'. Indeed, SiN perception abilities develop until late childhood (≥ 10 years) due to maturation of the auditory system and attentional abilities.^{127,128} Moreover, our data showed that fewer subjects

had significant CTS in informational than non-informational SiN conditions for phrasal CTS, and in all SiN conditions for syllabic CTS, with values in the most challenging SiN condition (energetic and informational noise) that were ~50% lower than those in the noiseless condition. Accordingly, setting speech SNR to 3 dB appeared to have made the task challenging enough for children, while ensuring that they could keep their attention focused throughout the experiment.

The amount of data per condition was limited to 2.5 min. Although it may seem little, we evidenced in a previous study that on average, ~30 s of MEG suffice to uncover significant CTS.²⁸ Moreover, CTS was significant, when assessed non-parametrically within-participant, in most of our participants in the least challenging conditions (phrasal, 100 %; syllabic, 94%). Of note, more data was used to estimate the regression model mapping MEG data onto reconstructed speech temporal envelope. Indeed, the model used to estimate CTS in each condition was trained on the ~20 min of data from all other conditions. This procedure substantially improved the estimation of CTS compared with a procedure wherein the model was trained and tested in a cross-validation scheme on the data from each condition separately (data not shown). Still, longer data acquisition could have produced more stable CTS estimates, and perhaps stronger associations with reading scores.

Supplementary references

123. Daube, C., Giordano, B., Schyns, P. & Ince, R. Quantitatively comparing predictive models with the Partial Information Decomposition. *2019 Conference on Cognitive Computational Neuroscience* (2019) doi:10.32470/ccn.2019.1142-0.
124. Jaworska, K. *et al.* Healthy ageing delays the neural processing of face features relevant for behaviour by 40 ms. *BioRxiv* **3260092**, (2019).
125. Nichols, T. E. & Holmes, A. P. Nonparametric permutation tests for functional neuroimaging: a primer with examples. *Hum. Brain Mapp.* **15**, 1–25 (2002).
126. Picard, M. & Bradley, J. S. Revisiting speech interference in classrooms. *Audiology* **40**, 221–244

(2001).

127. Thompson, E. C., Woodruff Carr, K., White-Schwoch, T., Otto-Meyer, S. & Kraus, N. Individual differences in speech-in-noise perception parallel neural speech processing and attention in preschoolers. *Hear. Res.* **344**, 148–157 (2017).
128. Sanes, D. H. & Woolley, S. M. N. A behavioral framework to guide research on central auditory development and plasticity. *Neuron* **72**, 912–929 (2011).

Supplementary tables and figures

Table S1. Nature of the information about reading abilities brought by each of the 3 uncovered features of the cortical tracking of speech (CTS) in noise and phonological awareness (mean of the scores for phoneme fusion and suppression). Significant values ($p < 0.05$) are displayed in boldface and marginally significant values are displayed in boldface and italicized.

	redundant		unique for phonological awareness		unique for the feature of CTS in noise		synergic	
	info	<i>p</i>	info	<i>p</i>	info	<i>p</i>	info	<i>p</i>
informational modulation in phrasal <i>nCTS</i>	0.0011	0.57	0.148	0.013	0.160	0.006	<i>0.0073</i>	<i>0.097</i>
visual modulation in phrasal <i>nCTS</i>	0.0066	0.30	<i>0.109</i>	<i>0.057</i>	0.155	0.011	0.0061	0.33
visual modulation in syllabic <i>nCTS</i>	0.048	0.0006	0.085	0.16	0.116	0.036	0.032	0.001

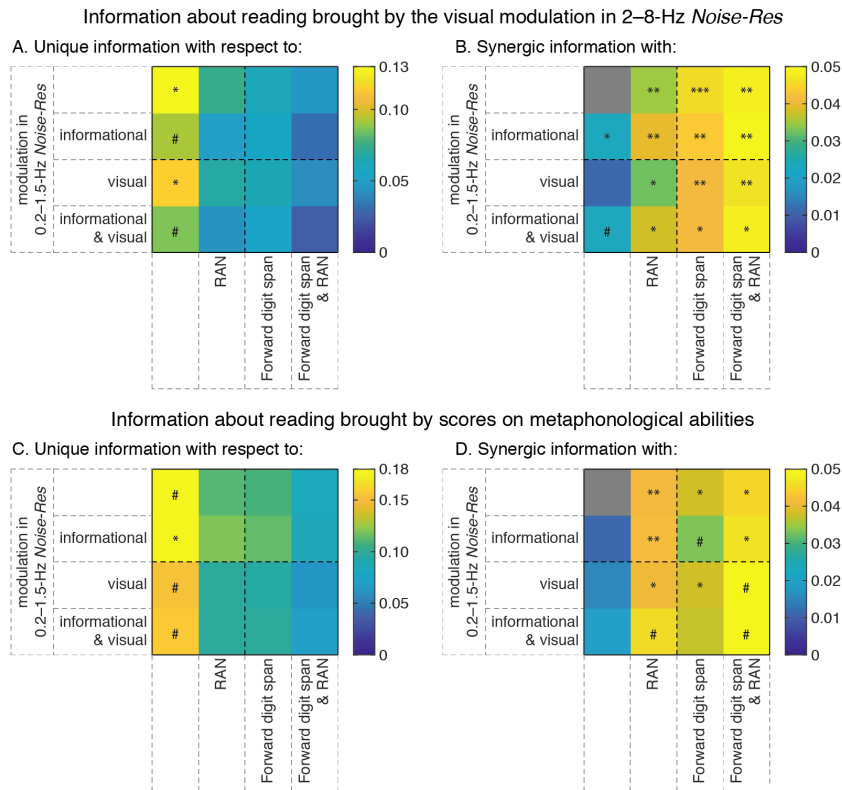


Figure S1. Nature of the information about reading brought by the visual modulation in normalized cortical tracking of speech (*nCTS*) at syllabic rate (**A** & **B**) and metaphonological abilities (**C** & **D**). **A** & **C** — Unique information with regard to each possible combination of the 4 regressors included in the final model of reading abilities (without RAN: columns 1 and 3; with RAN: columns 2 and 4; without forward digit span: columns 1 and 2; with forward digit span: columns 3 and 4; without the informational modulation in phrasal *nCTS*: rows 1 and 3; ...). **B** & **D** — Same as **A** for the synergistic information with each possible combination of the 4 regressors. ** $p < 0.01$, * $p < 0.05$, # $p < 0.1$.