Supplementary Materials

**Linguistic features extracted from samples and automatic tools used to extract them**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Type** | **Linguistic domain** | **Features** | **Explanatory notes** | **Extraction tool** |
| **Lexico-syntactic (275)** | Word production & complexity (11) | 1. DESWLsy: mean number of syllables per word
2. DESWLsyd: sd of the mean number of syllables per word
3. DESWLlt: mean number of characters per word
4. DESWLltd: sd of the mean number of characters per word
5. WRDPOLc: mean polysemy for content words
6. WRDHYPn: mean hypernymy for nouns
7. WRDHYPv: mean hypernymy for verbs
8. WRDHYPnv: mean hypernymy for nouns and verbs
9. Sixltr: % words >6 letters
10. repeated\_content\_lemmas: % content words repeated in sample, lemmatized
11. repeated\_content\_and\_pronoun\_lemmas: % content words and pronouns repeated in sample, lemmatized
 | Polysemy is the number of different senses of a word, e.g.to *book* a ticket or read a *book.*Hypernymy is calculated according to the number of words superordinate to the target word in a taxonomic hierarchy (Graesser, Namara, Louwerse, & Cai, 2004). Both are calculated using the WordNet database. | 1-8 Coh-Metrix 3.0 (Graesser et al., 2004)9 LIWC2015 (Pennebaker, Boyd, Jordan, & Blackburn, 2015)10 & 11 TAACO 2.0.4 (Crossley, Kyle, & Dascalu, 2019) |
| Parts-of-speech (POS) (18) | 1. nouns: % Nouns
2. verbs: % Verbs
3. inflected\_verbs: % Inflected verbs
4. light: % Light verbs
5. function: % Function words
6. pronouns: % Pronouns
7. determiners: % Determiners
8. adverbs: % Adverbs
9. adjectives: % Adjectives
10. prepositions: % Prepositions
11. coordinate: % Coordinate conjunctions
12. subordinate: % Subordinate conjunctions
13. demonstratives: % Demonstratives
14. nvratio: Noun:verb ratio (nouns / verbs)
15. noun\_ratio: Noun ratio (nouns / (nouns + verbs))
16. prp\_ratio: Pronoun ratio (pronouns / (pronouns + nouns))
17. sub\_coord\_ratio: Subordinate:coordinate ratio (subordinate conjunctions / coordinate conjunctions)
18. NID: ‘not in dictionary’, % words that do not appear in the English dictionary
 | Features are part-of-speech counts (normalized by number of words) and ratios. | COVFEFE (Liaqat, Fraser, & Komeili, 2019), utilizes the Stanford POS tagger |
| Lexical richness (8) | 1. TTR: Type-token-ratio or *U/V*, where *U* is the number of unique words (types) and *V* is the total words used (tokens)
2. brunet: Brunét’s index or *V(U-0.165)*
3. honore: Honoré’s statistic or ﻿100log*N*/(1-(*N*1/*U*)) where *N*1 is the number of words used only once (hapax legomena). ﻿Calculates hapax legomena as a proportion of the total number of words used as an indication of richness.
4. MATTR\_10: Moving average TTR (window size = 10)
5. MATTR\_20: Moving average TTR (window size = 20)
6. MATTR\_30: Moving average TTR (window size = 30)
7. MATTR\_40: Moving average TTR (window size = 40)
8. MATTR\_50: Moving average TTR (window size = 50)
 | TTR is a measure of word re-use, indicating lexical richness. All features use content words only. Features 2-8 are approaches to measuring lexical richness that aim to avoid issues associated with samples of different lengths (Covington & McFall, 2010).  | COVFEFE (Liaqat et al., 2019) |
| Psycholinguistics (34) | 1. MRC\_Familiarity\_CW: mean familiarity rating per content word, Medical Research Council (MRC) norms
2. MRC\_Familiarity\_FW: as above for function words
3. MRC\_Familiarity\_AW: as above for all words
4. MRC\_Concreteness\_CW: mean concreteness rating per content word, MRC norms
5. MRC\_Concreteness\_FW: as above for function words
6. MRC\_Concreteness\_AW: as above for all words
7. MRC\_Imageability\_CW: mean imageability rating per content word, MRC norms
8. MRC\_Imageability\_FW: as above for function words
9. MRC\_Imageability\_AW: as above for all words
10. MRC\_Meaningfulness\_CW: mean meaningfulness rating per content word, MRC norms
11. MRC\_Meaningfulness\_FW: as above for function words
12. MRC\_Meaningfulness\_AW: as above for all words
13. Kuperman\_AoA\_CW: mean age-of-acquisition rating per content word, Kuperman norms
14. Kuperman\_AoA\_FW: as above for function words
15. Kuperman\_AoA\_AW: as above for all words
16. Brysbaert\_Concreteness\_Combined\_CW: mean concreteness rating per content word, Brysbaert norms
17. Brysbaert\_Concreteness\_Combined\_FW: as above for function words
18. Brysbaert\_Concreteness\_Combined\_AW: as above for all words
19. SUBTLEXus\_Freq\_CW: mean frequency rating per content word, SUBTL norms from the SUBTLEXus corpus
20. SUBTLEXus\_Freq\_FW: as above for function words
21. SUBTLEXus\_Freq\_AW: as above for all words
22. SUBTLEXus\_Range\_CW: mean range per content word according to SUBTLEXus corpus.
23. SUBTLEXus\_Range\_FW: as above for function words
24. SUBTLEXus\_Range\_AW: as above for all words
25. BNC\_Spoken\_Freq\_CW: mean frequency rating per content word, British National Corpus (BNC) 2007 (spoken) corpus
26. BNC\_Spoken\_Freq\_FW: as above for function words
27. BNC\_Spoken\_Freq\_AW: as above for all words
28. BNC\_Spoken\_Range\_CW: mean range per content word according to BNC 2007 (spoken) corpus
29. BNC\_Spoken\_Range\_FW: as above for function words
30. BNC\_Spoken\_Range\_AW: as above for all words
31. BNC\_Spoken\_Bigram\_Normed\_Freq: mean frequency for bigrams according to BNC 2007 (spoken) corpus
32. BNC\_Spoken\_Bigram\_Proportion: proportion of bigrams in transcript that are within the most frequent 50,000 bigrams of the BNC 2007 (spoken) corpus
33. BNC\_Spoken\_Trigram\_Normed\_Freq: mean frequency for trigrams according to BNC 2007 (spoken) corpus
34. BNC\_Spoken\_Trigram\_Proportion: proportion of trigrams in transcript that are within the most frequent 50,000 bigrams of the BNC 2007 (spoken) corpus
 | Psycholinguistics indicate lexical sophistication by measuring different phenomena associated with words in the lexicon, and are assembled from different huma ratings. Familiar words are more known to users of the language. Concrete words are associated with the five senses, i.e. we can hear/ see/ feel/ smell or touch it, as opposed to abstract words. Imageability is the degree to which an image of the word can be created.Meaningfulness measures how related a word is to other words. Age-of-acquisition is the age at which language learners are usually exposed to a word.Frequency count features use a large reference corpus, e.g. BNC Consortium 2007, to estimate the frequency of each word. The SUBTLEXus corpus calculates word usage across subtitles from film and television (Brysbaert & New, 2009). Not all words will have an associated score for each measure, and these words are excluded from the total count when averaging.Range indices are a different approach to measuring frequency. The range of a word is the number of documents it appears in, i.e. how widely a word is used (Kyle & Crossley, 2015). | TAALES 2.2 (Kyle & Crossley, 2015; Kyle, Crossley, & Berger, 2018) |
| Psychological processes (50) | 1. Analytic: reflecting academic/ analytical thinking (Pennebaker, Chung, Frazee, Lavergne, & Beaver, 2014)
2. Clout: reflecting social standing or ‘rank’ (Kacewicz, Pennebaker, Davis, Jeon, & Graesser, 2014)
3. Authentic: reflecting truth (Newman, Pennebaker, Berry, & Richards, 2003)
4. Tone: reflecting emotional tone (Cohn, Mehl, & Pennebaker, 2004)
5. affect e.g. happy, cried
6. posemo: positive emotion e.g. love, sweet
7. negamo: negative emotion e.g. hurt, nasty
8. anx: anxiety e.g. worried
9. anger e.g. hate, kill
10. sad e.g. crying
11. social: social processes e.g. mate, talk
12. family e.g. daughter, dad
13. friend e.g. buddy
14. female: female references e.g. girl, her
15. male: male references e.g. boy, his
16. cogproc: cognitive processes e.g. know
17. insight e.g. think, know
18. cause: causation e.g. because, effect
19. discrep: discrepancy e.g. should, would
20. tentat: tentative e.g. maybe, perhaps
21. certain: certainty e.g. always, never
22. differ: differentiation e.g. but, else
23. percept: perceptual processes e.g. look, heard
24. see e.g. view, saw
25. hear e.g. listen, hearing
26. feel e.g. feels, touch
27. bio: biological processes e.g. eat, pain
28. body e.g. cheeks, hands
29. health e.g. clinic, flu
30. sexual e.g. love, incest
31. ingest e.g. dish, pizza
32. drives
33. affiliation e.g. ally, friend
34. achieve: achievement e.g. win, success
35. power e.g. superior, bully
36. reward e.g. take, prize
37. risk e.g. danger, doubt
38. focuspast: words focused on the past e.g. ago, did
39. focuspresent: words focused on the present e.g. today, now
40. focusfuture: words focused on the future e.g. may, soon
41. relativ: relativity e.g. area, bend
42. motion e.g. arrive, go
43. space e.g. down, in
44. time e.g. end, season
45. work e.g. job, majors
46. leisure e.g. cook, chat
47. home e.g. kitchen
48. money e.g. cash, owe
49. relig: religion e.g. alter, church
50. death e.g. bury, coffin
 | 1-4 are summary linguistic variables derived from previous research from the LIWC lab and converted to a % score. 5-50 are the % words in the sample relating to psychological constructs and personal concerns according to LIWC2015 internal dictionary of word categories. The same word can appear in multiple categories. Definitions supplied where required.  | LIWC2015 (Pennebaker et al., 2015) |
| Syntactic structures & complexity (32) | 1. WordCount: Total number of words
2. S: Total number of sentences
3. VP: Number of verb phrases normalized by total words (verb phrases/ words)
4. C: Number of clauses normalized by total words (clauses / words).
5. T: Number of T-units normalized by total words (T-units/ words).
6. DC: Number of dependent clauses normalized by total words (dependent clauses/ words).
7. CP: Number of coordinate phrases normalized by total words (coordinate phrases/ words)
8. CN: Number of complex nominals normalized by total words (complex nominals/ words)
9. CT\_A: Clauses per T-unit

**Length of production:**1. MLC: Mean length of clause (﻿words / clauses)
2. MLS: Mean length of sentence (﻿words / sentences)
3. MLT: Mean length of T-unit (﻿words / T-units)

**Sentence complexity:**1. CS: Sentence complexity ratio (clauses per sentence or ﻿clauses/sentences)

**Amount of subordination:**1. CT: T-unit complexity ratio (clauses per T-unit)
2. CTT: Complex T-unit ratio (complex T-units per T-unit)
3. DCC: Dependent clause ratio (dependent clauses per clause)
4. DCT: Dependent clauses per T-unit

**Amount of coordination:**1. CPC: Coordinate phrases per clause
2. CPT: Coordinate phrases per T-unit
3. TS: T-units per sentence

﻿**Relationship between syntactic structures and larger production units:**1. CNC: Complex nominals per clause
2. CNT: Complex nominals per T-unit
3. VPT: Verb phrases per T-unit
4. PP\_type\_rate: rate of prepositional phrases (PP/words)
5. PP\_type\_prop: proportion of prepositional phrases (PP length/words)
6. VP\_type\_rate: rate of verb phrases (VP/words)
7. VP\_type\_prop: proportion of verb phrases (VP length/words)
8. NP\_type\_rate: rate of noun phrases (NP/words)
9. NP\_type\_prop: proportion of noun phrases (NP length/words)
10. average\_PP\_length: words in prepositional phrases/ total prepositional phrases across sample
11. average\_VP\_length: as above for verb phrases
12. average\_NP\_length: as above for noun phrases
 | Clauses correspond to a subject and predicate, and all its modifiers.A T-unit corresponds to a main clause and all attached dependent clauses. A complex T-unit contains a dependent clause.A dependent clause contains a subject and a verb but cannot constitute a sentence alone.Complex nominals occur when a head noun is preceded by a modifier.Headings in bold correspond to five categories determined by Lu (2010). | COVFEFE (utilizes Lu’s Syntactic Complexity Analyzer (SCA, (Lu, 2010)) for features 1 – 23) |
| Syntactic parse tree features (4) | 1. maxdepth: Maximum Yngve depth of each parse tree, averaged over all sentences
2. totaldepth: Total sum of the Yngve depths for each parse tree, averaged over all sentences
3. meandepth: Mean Yngve depth of the parse tree, averaged over all sentences
4. treeheight: Average height of parse trees across all sentences
 | Calculations based on the Yngve depth for each word in a top-down, left-to-right syntax tree of a parsed sentence. It is a measure of embeddedness, or the ‘stack’ at each word (Yngve, 1960). The score increases as embeddedness increases, and features are different calculations based on the score.  | COVFEFE (Liaqat et al., 2019), utilizes the Stanford parser |
| Grammatical constituents of syntax tree (111) | 1. ROOT\_gt\_S
2. NP\_gt\_DT\_NN
3. PP\_gt\_IN\_NP
4. S\_gt\_NP\_VP
5. NP\_gt\_PRP
6. NP\_gt\_NNS
7. S\_gt\_NP\_VP\_A
8. S\_gt\_VP
9. PRT\_gt\_RP
10. ADVP\_gt\_RB
11. NP\_gt\_NP\_PP
12. NP\_gt\_DT\_NNS
13. S\_gt\_CC\_NP\_VP
14. VP\_gt\_VBZ\_VP
15. NP\_gt\_NN
16. ROOT\_gt\_NP
17. SBAR\_gt\_S
18. VP\_gt\_TO\_VP
19. NP\_gt\_DT
20. S\_gt\_VP\_A
21. NP\_gt\_DT\_NN\_NN
22. NP\_gt\_DT\_JJ\_NN
23. VP\_gt\_VBZ\_NP
24. VP\_gt\_VB\_NP
25. VP\_gt\_VBG\_NP
26. ROOT\_gt\_FRAG
27. NP\_gt\_PRP$\_NN
28. VP\_gt\_VBP\_NP
29. VP\_gt\_VB
30. NP\_gt\_FW
31. NP\_gt\_NP\_VP
32. SBAR\_gt\_IN\_S
33. NP\_gt\_NP\_CC\_NP
34. ADJP\_gt\_JJ
35. VP\_gt\_VBG\_PP
36. NP\_gt\_JJ\_NN
37. VP\_gt\_VBP
38. NP\_gt\_NP\_SBAR
39. NP\_gt\_NP\_VP\_A
40. VP\_gt\_VBP\_SBAR
41. S\_gt\_ADVP\_NP\_VP
42. VP\_gt\_VBP\_S
43. SBAR\_gt\_WHNP\_S
44. VP\_gt\_MD\_VP
45. PP\_gt\_TO\_NP
46. VP\_gt\_VP\_CC\_VP
47. VP\_gt\_VBZ
48. VP\_gt\_VBZ\_S
49. VP\_gt\_VBG
50. VP\_gt\_VBG\_S
51. WHNP\_gt\_WP
52. NP\_gt\_NNP
53. VP\_gt\_VBP\_VP
54. VP\_gt\_VBG\_PRT
55. FRAG\_gt\_CC\_NP
56. NP\_gt\_NP\_SBAR\_A
57. VP\_gt\_VB\_S
58. S\_gt\_S\_CC\_S
59. VP\_gt\_VBZ\_PP
60. ADVP\_gt\_RB\_RB
61. VP\_gt\_VBG\_PRT\_PP
62. VP\_gt\_VBZ\_ADJP
63. NP\_gt\_NP\_NP
64. NP\_gt\_RB
65. NP\_gt\_NN\_NN
66. VP\_gt\_VBD\_NP
67. WHNP\_gt\_WDT
68. NP\_gt\_NN\_NNS
69. VP\_gt\_VB\_NP\_PP
70. NP\_gt\_NP\_PP\_A
71. NP\_gt\_PRP$\_NNS
72. NP\_gt\_NP\_NP\_A
73. NP\_gt\_EX
74. INTJ\_gt\_UH
75. NP\_gt\_DT\_JJ\_NNS
76. S\_gt\_INTJ\_VP
77. VP\_gt\_VB\_VP
78. NP\_gt\_CD\_NNS
79. VP\_gt\_VBG\_NP\_PP
80. VP\_gt\_VBD\_SBAR
81. VP\_gt\_VB\_PP
82. VP\_gt\_VBN\_PP
83. ADJP\_gt\_RB\_JJ
84. VP\_gt\_VBZ\_SBAR
85. WHADVP\_gt\_WRB
86. FRAG\_gt\_ADJP
87. SBAR\_gt\_WHADVP\_S
88. VP\_gt\_VBP\_PP
89. S\_gt\_NP\_ADJP
90. S\_gt\_NP\_ADVP\_VP
91. NP\_gt\_DT\_DT\_NN
92. PP\_gt\_IN
93. VP\_gt\_VBD\_VP
94. NP\_gt\_CD
95. VP\_gt\_VBN\_NP
96. S\_gt\_NP\_NP
97. PP\_gt\_IN\_PP
98. ROOT\_gt\_INTJ
99. ROOT\_gt\_SBARQ
100. S\_gt\_CC\_NP\_VP\_A
101. VP\_gt\_VBG\_PRT\_NP
102. VP\_gt\_VB\_ADJP
103. VP\_gt\_VBZ\_NP\_PP
104. NP\_gt\_PRP$\_JJ\_NN
105. NP\_gt\_DT\_FW
106. NP\_gt\_JJ\_NNS
107. ADJP\_gt\_JJ\_PP
108. ADVP\_gt\_RB\_PP
109. VP\_gt\_VB\_SBAR
110. PP\_gt\_IN\_S
111. NP\_gt\_CD\_NN
 | Constituents comprising the syntactic parse tree are quantified and normalized by the total number of constituents in the sample. For example NP\_gt\_DT\_NN represents a noun phrase (NP) comprised of a determiner (DT) and noun (NN), usually denoted NP -> DT NN.Tags are from the Penn Treebank, see [https://web.archive.org/web/20130517134339/http://bulba.sdsu.edu/jeanette/thesis/PennTags.html](https://web.archive.org/web/20130517134339/http%3A//bulba.sdsu.edu/jeanette/thesis/PennTags.html) for a full list of clause and phrase level tags.Word level tagsCC - Coordinating conjunctionCD - Cardinal numberDT - DeterminerEX - Existential thereFW - Foreign wordIN - Preposition or subordinating conjunctionJJ - AdjectiveJJR - Adjective, comparativeJJS - Adjective, superlativeLS - List item markerMD - ModalNN - Noun, singular or massNNS - Noun, pluralNNP - Proper noun, singularNNPS - Proper noun, pluralPDT - PredeterminerPOS - Possessive endingPRP - Personal pronounPRP$ - Possessive pronoun (prolog version PRP-S)RB - AdverbRBR - Adverb, comparativeRBS - Adverb, superlativeRP - ParticleSYM - SymbolTO - toUH - InterjectionVB - Verb, base formVBD - Verb, past tenseVBG - Verb, gerund or present participleVBN - Verb, past participleVBP - Verb, non-3rd person singular presentVBZ - Verb, 3rd person singular presentWDT - Wh-determinerWP - Wh-pronounWP$ - Possessive wh-pronoun (prolog version WP-S)WRB - Wh-adverb | COVFEFE (Liaqat et al., 2019) |
| Shannon entropy (1) | 1. Entropy: H 2 ( X ) = − ∑ i = 1 n c o u n t i N log 2 ⁡ ( c o u n t i N ) Entropy for letters, given below, where *N* is total letters and *counti* is the count of letter*i*,

$$\sum\_{i=1}^{n}\frac{count\_{i}}{N}log\_{2}\left(\frac{count\_{i}}{N}\right)$$ | Entropy, arising from information theory and applied here to letters, is a measure of information inherent in the sample. It indicates certainty with which an unknown letter can be predicted based on previous known information (Shannon, 1951). | Python script\* |
| Fluency (3) | 1. False\_starts\_ratio: false starts/total outputs
2. Filler\_ratio: fillers/total outputs
3. Nonspecifics\_ratio: ‘thing’ words/words
 | False starts correspond to words that are started but not completed, e.g. “he looks **nau=** naughty”.Fillers correspond to ‘um’, ‘ah’, ‘er’ and their variations.Non-specific ‘thing’ words are thing, some*thing*, any*thing* | Python script\* |
| Non-verbal (3) | 1. Laughter: Count of laughter normalized by ‘total outputs’ i.e. words + laughter + pauses (laughter/total outputs)
2. Pauses\_ratio: As above for pauses (pauses/total outputs)
3. QMark: Count of the number of questions asked according to instances of ‘?’
 | Laughter and pauses were annotated at the transcription stage by the transcriber. Duration was not recorded. | 1 & 2 Python script\*3 LIWC2015 (Pennebaker et al., 2015) |
| **Semantic (11)** | Semantic content (3) | 1. Idea\_density: Propositional idea density
2. prop\_density: Similar to above, calculates how dense a sample is with propositions using the following -(verbs+adjectives+adverbs+prepositions+conjunctions)/ words
3. content\_density: Calculates how dense with content bearing words a sample is using - (nouns+verbs+adjectives+adverbs)/words
 | Idea density is a measure of how dense a sample is with ‘ideas’, based on POS tags. CPIDR 3.2 propositions roughly correspond to ﻿verbs, adjectives, adverbs, prepositions and conjunctions. Certain rules are applied to make adjustments prior to the calculation stage and has been found to closely match human ratings (Brown, Snodgrass, Kemper, Herman, & Covington, 2008) | 1 CPIDR 3.2 (Brown et al., 2008)2 & 3 (Liaqat et al., 2019) |
| Semantic coherence (8) | 1. Mean\_cosine
2. Mean\_cosine\_1
3. sd\_cosine\_1
4. Mean\_cosine\_2
5. sd\_cosine\_2
6. Mean\_cosine\_4
7. sd\_cosine\_4
8. Mean\_wmd: average Word Movers Distance between adjacent sentences
 | Features utilize semantic space word vector representations to explore semantic coherence. Vectors are pre-trained word2vec model using the Google News corpus (Mikolov, Chen, Corrado, & Dean, 2013). Features 1-7 calculate mean cosine similarity between adjacent sentences and moving windows, and standard deviation (sd) of the mean as a measure of variability. Word Movers Distance (WMD) calculates the minimum cumulative distance needed to travel between word vectors of adjacent sentences as a measure of similarity (Kusner, Sun, Kolkin, & Weinberger, 2015). | Python script\* |

 \*Python scripts are available at https://github.com/natasha-clarke/CCD-Study.git

**Full results for HC vs. AD+MCI classification using different connected speech tasks and univariate or multivariate feature selection approaches**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|   |   | **PD** | **CS** | **ONR** | **PR** | **NNR** |
| **All features** | Accuracy | 0.78 (0.13) | 0.68 (0.08) | 0.80 (0.12) | 0.60 (0.19) | 0.58 (0.13) |
| Sensitivity | 0.69 (0.30) | 0.62 (0.29) | 0.71 (0.31) | 0.66 (0.23) | 0.67 (0.23) |
| Specificity | 0.85 (0.15) | 0.80 (0.20) | 0.90 (0.15) | 0.59 (0.30) | 0.58 (0.35) |
| AUC | 0.83 (0.07) | 0.72 (0.14) | 0.85 (0.11) | 0.76 (0.27) | 0.67 (0.13) |
| ***k*=5** | Accuracy | 0.58 (0.11) | 0.56 (0.11) | 0.68 (0.15) | 0.54 (0.15) | 0.58 (0.18) |
| Sensitivity | 0.46 (0.09) | 0.56 (0.11) | 0.64 (0.17) | 0.58 (0.29) | 0.50 (0.26) |
| Specificity | 0.72 (0.24) | 0.60 (0.20) | 0.75 (0.27) | 0.55 (0.33) | 0.68 (0.11) |
| AUC | 0.73 (0.12) | 0.70 (0.13) | 0.75 (0.16) | 0.63 (0.21) | 0.65 (0.13) |
| ***k*=10** | Accuracy | 0.66 (0.13) | **0.66 (0.11)** | 0.72 (0.13) | 0.50 (0.19) | **0.62 (0.16)** |
| Sensitivity | 0.60 (0.30) | **0.62 (0.10)** | 0.68 (0.22) | 0.56 (0.31) | **0.53 (0.21)** |
| Specificity | 0.76 (0.16) | **0.78 (0.31)** | 0.79 (0.15) | 0.47 (0.34) | **0.72 (0.11)** |
| AUC | 0.70 (0.14) | **0.74 (0.10)** | 0.81 (0.10) | 0.67 (0.29) | **0.62 (0.10)** |
| ***k*=20** | Accuracy | 0.60 (0.10) | 0.62 (0.13) | 0.62 (0.25) | 0.58 (0.24) | 0.58 (0.19) |
| Sensitivity | 0.58 (0.16) | 0.53 (0.30) | 0.71 (0.09) | 0.65 (0.27) | 0.57 (0.29) |
| Specificity | 0.57 (0.19) | 0.79 (0.29) | 0.61 (0.38) | 0.53 (0.39) | 0.58 (0.32) |
| AUC | 0.69 (0.15) | 0.66 (0.19) | 0.69 (0.26) | 0.71 (0.25) | 0.60 (0.37) |
| ***k*=40** | Accuracy | 0.72 (0.15) | 0.56 (0.09) | 0.66 (0.17) | 0.68 (0.19) | 0.46 (0.11) |
| Sensitivity | 0.73 (0.22) | 0.42 (0.25) | 0.53 (0.28) | 0.74 (0.20) | 0.47 (0.33) |
| Specificity | 0.64 (0.20) | 0.79 (0.29) | 0.79 (0.24) | 0.61 (0.42) | 0.48 (0.16) |
| AUC | 0.77 (0.12) | 0.70 (0.10) | 0.73 (0.22) | 0.80 (0.25) | 0.54 (0.22) |
| **10RFE-LogR** | Accuracy | **0.76 (0.18)** | 0.60 (0.14) | **0.78 (0.08)** | **0.74 (0.15)** | 0.56 (0.09) |
| Sensitivity | **0.69 (0.30)** | 0.67 (0.16) | **0.75 (0.23)** | **0.78 (0.15)** | 0.56 (0.15) |
| Specificity | **0.81 (0.12)** | 0.51 (0.32) | **0.82 (0.21)** | **0.74 (0.25)** | 0.58 (0.14) |
| AUC | **0.84 (0.11)** | 0.68 (0.12) | **0.84 (0.05)** | **0.85 (0.19)** | 0.66 (0.17) |

10RFE-LogR = Recursive feature elimination (with a step size of 1) combined with logistic regression to select 10 features. PD = picture description, CS = conversational speech, ONR = overlearned narrative, PR = procedural recall, NNR = novel narrative recall. Results in bold are highest accuracies using feature selection (and associated sensitivity, specificity and AUC) for each speech task, presented in the main paper.

**Full results for HC vs AD classification using different connected speech tasks and univariate or multivariate feature selection approaches**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|   |   | **PD** | **CS** | **ONR** | **PR** | **NNR** |
| **All features** | Balanced accuracy | 0.59 (0.24) | 0.72 (0.12) | 0.77 (0.18) | 0.52 (0.20) | 0.69 (0.18) |
| Sensitivity | 0.40 (0.42) | 0.52 (0.15) | 0.58 (0.28) | 0.38 (0.26) | 0.63 (0.22) |
| Specificity | 0.78 (0.33) | 0.92 (0.12) | 0.95 (0.11) | 0.66 (0.23) | 0.75 (0.20 |
| AUC | 0.83 (0.23) | 0.86 (0.03) | 0.83 (0.18) | 0.65 (0.30) | 0.82 (0.17) |
| ***k*=5** | Balanced accuracy | 0.50 (0.19) | 0.62 (0.09) | 0.83 (0.15) | **0.68 (0.24)** | **0.70 (0.28)** |
| AUC | 0.58 (0.32) | 0.63 (0.19) | 0.91 (0.09) | **0.65 (0.25)** | **0.76 (0.27)** |
| Sensitivity | 0.33 (0.31) | 0.35 (0.22) | 0.75 (0.35) | **0.52 (0.46)** | **0.60 (0.42)** |
| Specificity | 0.67 (0.42) | 0.89 (0.15) | 0.91 (0.12) | **0.84 (0.15)** | **0.80 (0.15)** |
| ***k*=10** | Balanced accuracy | 0.47 (0.25) | 0.69 (0.20) | 0.85 (0.16) | 0.41 (0.09) | 0.71 (0.18) |
| Sensitivity | 0.30 (0.45) | 0.47 (0.36) | 0.75 (0.35) | 0.22 (0.22) | 0.65 (0.34) |
| Specificity | 0.63 (0.28) | 0.91 (0.12) | 0.95 (0.11) | 0.60 (0.14) | 0.76 (0.22) |
| AUC | 0.59 (0.36) | 0.80 (0.21) | 0.96 (0.06) | 0.46 (0.16) | 0.73 (0.26) |
| ***k*=20** | Balanced accuracy | 0.58 (0.25) | **0.75 (0.15)** | **0.90 (0.11)** | 0.42 (0.20) | 0.48 (0.20) |
| Sensitivity | 0.40 (0.42) | **0.62 (0.26)** | **0.83 (0.24)** | 0.27 (0.25) | 0.38 (0.26) |
| Specificity | 0.77 (0.22) | **0.88 (0.12)** | **0.96 (0.09)** | 0.56 (0.29) | 0.58 (0.25) |
| AUC | 0.61 (0.26) | **0.80 (0.23)** | **0.94 (0.06)** | 0.40 (0.31) | 0.65 (0.21) |
| ***k*=40** | Balanced accuracy | 0.48 (0.15) | 0.65 (0.21) | 0.74 (0.07) | 0.38 (0.18) | 0.67 (0.20) |
| Sensitivity | 0.33 (0.31) | 0.42 (0.28) | 0.53 (0.07) | 0.30 (0.45) | 0.68 (0.32) |
| Specificity | 0.63 (0.28) | 0.88 (0.16) | 0.95 (0.11) | 0.46 (0.15) | 0.65 (0.21) |
| AUC | 0.55 (0.24) | 0.64 (0.08) | 0.79 (0.13) | 0.40 (0.27) | 0.77 (0.21) |
| **10RFE-LogR** | Balanced accuracy | **0.59 (0.30)** | 0.58 (0.27) | 0.69 (0.13) | 0.55 (0.26) | 0.62 (0.15) |
| Sensitivity | **0.50 (0.35)** | 0.42 (0.28) | 0.43 (0.25) | 0.45 (0.37) | 0.52 (0.29) |
| Specificity | **0.68 (0.32)** | 0.75 (0.28) | 0.95 (0.11) | 0.65 (0.31) | 0.73 (0.22) |
| AUC | **0.75 (0.26)** | 0.68 (0.32) | 0.77 (0.14) | 0.65 (0.20) | 0.78 (0.24) |

10RFE-LogR = Recursive feature elimination (with a step size of 1) combined with logistic regression to select 10 features. PD = picture description, CS = conversational speech, ONR = overlearned narrative, PR = procedural recall, NNR = novel narrative recall. Results in bold are highest accuracies using feature selection (and associated sensitivity, specificity and AUC) for each speech task, presented in the main paper.

**Full results for HC vs MCI classification using different connected speech tasks and univariate or multivariate feature selection approaches**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|   |   | **PD** | **CS** | **ONR** | **PR** | **NNR** |
| **All features** | Balanced accuracy | 0.70 (0.21) | 0.62 (0.16) | 0.74 (0.15) | 0.63 (0.22) | 0.49 (0.20) |
| Sensitivity | 0.65 (0.42) | 0.60 (0.42) | 0.50 (0.35) | 0.47 (0.36) | 0.32 (0.21) |
| Specificity | 0.75 (0.15) | 0.65 (0.34) | 0.97(0.06) | 0.79 (0.14) | 0.67 (0.28) |
| AUC | 0.74 (0.24) | 0.62 (0.15) | 0.88 (0.22) | 0.70 (0.38) | 0.35 (0.21) |
| ***k*=5** | Balanced accuracy | 0.44 (0.20) | 0.57 (0.21) | 0.56 (0.17) | 0.31 (0.14) | 0.38 (0.16) |
| Sensitivity | 0.17 (0.24) | 0.27 (0.25) | 0.35 (0.42) | 0.00 (0.00) | 0.17 (0.24) |
| Specificity | 0.71 (0.28) | 0.88 (0.17) | 0.76 (0.16) | 0.63 (0.29) | 0.59 (0.30) |
| AUC | 0.46 (0.29) | 0.70 (0.35) | 0.70 (0.29) | 0.26 (0.08) | 0.27 (0.11) |
| ***k*=10** | Balanced accuracy | 0.57 (0.13) | 0.43 (0.25) | 0.70 (0.15) | 0.47 (0.23) | 0.33 (0.15) |
| Sensitivity | 0.37 (0.41) | 0.15 (0.22) | 0.52 (0.29) | 0.27 (0.43) | 0.07 (0.15) |
| Specificity | 0.78 (0.24) | 0.70 (0.31) | 0.88 (0.17) | 0.66 (0.24) | 0.60 (0.20) |
| AUC | 0.68 (0.21) | 0.51 (0.21) | 0.68 (0.17) | 0.50 (0.15) | 0.27 (0.20) |
| ***k*=20** | Balanced accuracy | 0.59 (0.17) | **0.70 (0.20)** | 0.67 (0.14) | 0.54 (0.20) | **0.43 (0.15)** |
| Sensitivity | 0.37 (0.41) | **0.58 (0.37)** | 0.47 (0.36) | 0.27 (0.43) | **0.30 (0.27)** |
| Specificity | 0.81 (0.19) | **0.82 (0.19)** | 0.88 (0.17) | 0.66 (0.24) | **0.56 (0.17)** |
| AUC | 0.67 (0.11) | **0.75 (0.10)** | 0.72 (0.20) | 0.49 (0.28) | **0.50 (0.23)** |
| ***k*=40** | Balanced accuracy | **0.62 (0.26)** | 0.56 (0.14) | 0.75 (0.20) | 0.44 (0.21) | 0.40 (0.12) |
| Sensitivity | **0.40 (0.42)** | 0.37 (0.22) | 0.62 (0.36) | 0.30 (0.45) | 0.27 (0.25) |
| Specificity | **0.84 (0.15)** | 0.76 (0.14) | 0.88 (0.17) | 0.59 (0.23) | 0.53 (0.23) |
| AUC | **0.77 (0.28)** | 0.63 (0.07) | 0.70 (0.28) | 0.47 (0.18) | 0.42 (0.16) |
| **10RFE-LogR** | Balanced accuracy | 0.59 (0.10) | 0.47 (0.20) | **0.78 (0.13)** | **0.52 (0.12)** | 0.35 (0.12) |
| Sensitivity | 0.37 (0.22) | 0.28 (0.39) | **0.67 (0.31)** | **0.43 (0.25)** | 0.00 (0.00) |
| Specificity | 0.80 (0.19) | 0.65 (0.31) | **0.90 (0.10)** | **0.60 (0.19)** | 0.70 (0.24) |
| AUC | 0.71 (0.22) | 0.53 (0.23) | **0.82 (0.22)** | **0.62 (0.21)** | 0.42 (0.25) |

10RFE-LogR = Recursive feature elimination (with a step size of 1) combined with logistic regression to select 10 features. PD = picture description, CS = conversational speech, ONR = overlearned narrative, PR = procedural recall, NNR = novel narrative recall. Results in bold are highest accuracies using feature selection (and associated sensitivity, specificity and AUC) for each speech task, presented in the main paper.

**Supplementary Materials References**

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