

[aMCI] versus nonamnesic [naMCI]; threshold $p < .05$).

Results: The sample included 599 participants with NC and 110 with CI (mean age = 72.3 ± 11.0 years, 54% female). The regression identified 8 linguistic features for IR and 7 for DR that significantly predicted cognitive status. Decreased use of content words related to work (e.g., employed, school, police) and biological processes (e.g., cook, cafeteria, eat) and the use of negations (e.g., no, not, can't) were predictive of cognitive impairment in both recall conditions. In contrast, the use of other content word categories were predictive of cognitive status in only one recall condition (IR: leisure, cognitive processes, space; DR: drives, number). The use of fewer prepositions in IR, more first-person pronouns in DR, and fewer words in the past tense in DR were each associated with cognitive impairment. Word count was not predictive of cognitive status. Both PFSs were highly associated with cognitive status (PFS_IR $\beta = 0.74$, $p < 0.001$; PFS_DR $\beta = 0.86$, $p = 0.001$) with high discriminative value (PFS_IR AUC = 0.93, sensitivity = 0.81, specificity = 0.91; PFS_DR AUC = 0.95, sensitivity = 0.77, specificity = 0.88). In the CI subset, linguistic features differed between those classified as aMCI ($n = 24$) and naMCI ($n = 40$). Two function word categories predicted aMCI in IR whereas decreased word count, two function word categories, and two content word categories predicted aMCI in DR (all $p < .05$).

Conclusions: Linguistic features from paragraph recall provide high predictive value for classifying cognitive status increasing its potential as a cognitive screener in clinical settings. Additionally, each recall condition identified unique linguistic features associated with cognitive impairment which may aid differentiation of cognitive impairment subtypes and elucidate processes underlying deficits in learning and recall.

Categories: Teleneuropsychology/ Technology

Keyword 1: assessment

Keyword 2: cognitive processing

Keyword 3: aging (normal)

Correspondence: Stacy L. Andersen, Boston University, stacy@bu.edu

96 Proof of Principle: Can Paragraph Recall Pauses and Speech Frequencies

Correctly Classify Cognitively Compromised Older Adults?

Leeor Hershkovich¹, Sabyasachi Bandyopadhyay¹, Jack Wittmayer¹, Patrick Tighe¹, David J Libon², Catherine C Price¹, Parisa Rashidi¹

¹University of Florida, Gainesville, FL, USA.

²Rowan University, Stratford, NJ, USA

Objective: Recent research has found that machine learning based analysis of patient speech can be used to classify Alzheimer's Disease. We know of no studies, however, which systematically explore the value of pausing events in speech for detecting cognitive limitations. Using retrospectively acquired voice data from paragraph memory tests, we created two types of pause features: a) the number and duration of pauses, and b) frequency components in speech immediately following pausing. Multiple machine learning models were used to assess how these features could effectively discriminate individuals classified into two groups: Cognitively Compromised versus Cognitively Well.

Participants and Methods: Participants (age > 65 years, $n = 67$) completed the Newcomer paragraph memory test and a neuropsychological protocol as part of a federally funded prospective IRB approved investigation at the University of Florida. Participant vocal recordings were acquired for the immediate and delay conditions of the test. Speaker diarization was performed on the immediate free recall test condition to separate voices of patients from examiners. Features extracted from both test conditions included a) 3 pause characteristics (total number of pauses, total pause duration, and length of the longest pause), and b) 20 Mel Frequency Cepstral Coefficients (MFCC) pertaining to speech immediately (2.7 seconds) following pauses. These were combined with demographics (age, sex, race, education, and handedness) to create a total of 105 features that were used as inputs for multiple machine learning analytic models (random forest, logistic regression, naïve Bayes, AdaBoost, Gradient Boost, and multi-layered perceptron). External neuropsychological metrics were used to initially classify Cognitively Compromised (i.e., < -1.0 standard deviation on > two of five test metrics: total immediate, delay, discrimination Hopkins Verbal Learning Test-Revised (HVLT-R),

Controlled Oral Word Association (COWA) test, category fluency ('animals')). Pearson Product Moment Correlations were used to assess the linear relationships between pauses and speech frequency categories and neuropsychological metrics.

Results: Neuropsychology metric classification using -1SD cut-off identified 27% (18/67 participants) as Cognitively Compromised. The Cognitively Compromised group and the Cognitively Well group did not show any difference in distributions of individual pause/frequency features (Mann Whitney U-test, $p > 0.11$). A negative correlation was found between total duration of short pauses and HVLt total immediate free recall, while a positive correlation was found between MFCC-10 and HVLt total immediate free recall. The best classification model was AdaBoost Classifier which predicted the Cognitively Compromised label with 0.91 area under receiver operating curve, 0.81 accuracy, 0.43 sensitivity, 1.0 specificity, 1.0 precision, 0.6 f1 score.

Conclusions: Pause characteristics and frequency profiles of speech immediately following pauses from a paragraph memory test accurately identified older adults with compromised cognition, as measured by verbal learning and verbal fluency metrics. Furthermore, individuals with reduced HVLt immediate free recall generated more pauses, while individuals who recalled more words had higher power in mid-frequency bands (10th MFCC). Future research needs to replicate how paragraph recall pause characteristics and frequency the profile of speech immediately following pauses potentially provides a low resource alternative to automatic speech recognition models for detecting cognitive impairments.

Categories: Teleneuropsychology/ Technology

Keyword 1: assessment

Keyword 2: cognitive processing

Keyword 3: aging (normal)

Correspondence: Leeor Hershkovich,
University of Florida,
Leeor.Hershkovich@gmail.com

93 Digitized Trail Making Test in the NKI-Rockland Sample Normative Lifespan Neuroimaging Study

Anna MacKay-Brandt¹, Nadine Schwab², Irene Piryatinsky³, Maxine Krengel⁴, Malvina Pietrzykowski⁵, Dave Gansler⁵, Andrea Suazo Rivas¹, Alyssa DiFalco¹, Stan Colcombe¹

¹Nathan Kline Institute for Psychiatric Research, Orangeburg, NY, USA. ²Harvard University, Boston, MA, USA. ³Tufts University, Boston, MA, USA. ⁴Boston University, Boston, MA, USA. ⁵Suffolk University, Boston, MA, USA

Objective: Digitized cognitive assessment captures rich behavioral information that remains unmeasured using conventional methods. Data capture tools recently accessible only in specialized laboratories are now feasible at scale using off-the-shelf tablet devices. This study aims to share data from a digitized cognitive assessment embedded in an open-science research program collecting extensive neuroimaging, health, behavioral, neuropsychological, and psychiatric characterizations to advance translational cognitive neuroscience. In this research we present normative performance metrics from a digital version of the Trail Making Test.

Participants and Methods: The NKI-Rockland Sample (NKI-RS) has provided a model for openly-shared lifespan normative neuroimaging resources contributed by a community-ascertained sample ($n=1,500$, aged 6-85) and generating over 400 publications across diverse research areas. The next generation NKI-RS study (recruitment target= 600, aged 9-75) aims to enrich these resources for brain-behavioral research, normative reference, and biomarker discovery. One focus of innovation is the inclusion of digitized cognitive assessments (DCAs) utilizing an open-resource task development and data collection platform (Mindlogger, Child Mind Institute). We present preliminary data from a digitized version of the Trail Making Tests and report early descriptive metrics. The TMTs was administered via an iPad Pro using an Apple pen as part of a laboratory-based EEG procedure. The TMTs follows standard administration instructions, including a practice sample before each test condition. Error feedback is included in the task implementation such that an incorrect connection is marked with an "x" and the participant is directed to the last correct circle to continue. Feedback is automated within the task. Pixel-level spatial resolution and millisecond timing is captured across all drawing tasks. Task design, implementation, and