metrics with spatial segregation to parse circle connection time from dwell time within a circle. Interestingly, dwell time, rather than traditional total time to completion, was the strongest predictor of differences between conditions and across age.
Baliga and colleagues present data on a protocol of novel cancellation tests. Memory clinic patients were classified into groups presenting with mild dementia, mild cognitive impairment, and those who were cognitively normal. Digital parameters of interest included correct responses, commissions, mean intra-response latency, and mean apple pencil touch. Using these parameters, significant between group differences were obtained. Moreover, logistic regression analyses were able to classify patients into their respective groups.
It is well understood that paragraph recall tests assess a variety of underlying cognitive abilities. Andersen and colleagues studied Logical Memory recall in the Long-Life Family Study and extracted linguistic parameters that included word count, grammatical features (e.g., prepositions), and content words related to specific categories (e.g., work). Participants were classified as cognitively normal or impaired. Analyses identified distinct linguistic features of free recall that predicted cognitive status.
Hershkovich and colleagues extract measured pauses and speech frequency behavior also from a paragraph recall test. A combination of paragraph recall pause duration, speech frequency parameters, and demographic variables were able to classify older adults with and without cognitive compromise. Collectively, the evidence provided in this series of papers demonstrates that digital platforms can capture and quantify highly nuanced neurocognitive behavior to enrich information available to researchers and clinicians for analysis and clinical formulations. Digital assessment technology holds promise to realize the vision of the Boston Process Approach and revolutionize neuropsychological assessment.

Keyword 1: assessment
Keyword 2: cognitive processing
Keyword 3: aging (normal)

95 Delving Beyond the Test Score: Linguistic Markers of Cognitive Impairment on Paragraph Recall

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Objective: Cognitive tests requiring spoken responses, such as paragraph recall, are rich in cognitive-related information that is not captured using traditional scoring methods. This study aimed to determine if linguistic features embedded in spoken responses may differentiate between individuals who are and are not cognitively impaired.
Participants and Methods: Participants in the Long Life Family Study completed a neuropsychological assessment which included the WMS-R Logical Memory I paragraph recall. For a subset of participants (N=709), test responses were digitally recorded and manually transcribed. We used Linguistic Inquiry Word Count, a text analysis program, to quantify word counts, grammatical features (e.g, prepositions, verb tenses), and the use of content words related to specific semantic categories (e.g., work-related, numbers) for immediate (IR) and delayed recall (DR). We used regression models with Generalized Estimating Equations adjusted by age, sex, education, and within-family correlation to select features associated with cognitive status (normal cognition [NC] versus cognitive impairment [CI]; Bonferroni-corrected threshold $p<0.001$). Next, we developed a “polyfeature score” (PFS) for both immediate and delayed recall, each calculated as a weighted sum of the selected linguistic features. We then built a logistic regression model to evaluate the predictive value of each PFS for identifying cognitively impaired individuals. In secondary analyses, we used regression models as above to identify features associated with mild cognitive impairment subtype (amnestic

[aMCI] versus nonamnestic [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 β= 0.74, p< 0.001; PFS_DR β= 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
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96 Proof of Principle: Can Paragraph Recall Pauses and Speech Frequencies Correctly Classify Cognitively Compromised Older Adults?

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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),

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