Impaired Retest Learning Identifies Individuals At Risk Of Cognitive Decline:

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Abstract:
Background: Measures of longitudinal cognitive performance in older adults reflect two opposing processes: progressive cognitive decline and retest learning. While some groups use alternate test forms or statistical procedures to reduce retest learning effects, impaired retest learning may reflect reduced cognitive plasticity occurring early in neurodegenerative disease (e.g., Duff et al., 2011; Jonaitis, et al., 2019) and hence add diagnostic sensitivity. Here, we examined whether impaired retest learning predicted subsequent cognitive decline.
Methods: Predominantly older participants (N = 572; mean age = 65.9, SD = 10.7 years; 56.8% female; 39.2% White; 35.8% college-educated) completed the California Cognitive Assessment Battery (CCAB) in their homes. CCAB is a telemedically-proctored computerized test battery that includes automated scoring of speech and language metrics. We extracted 71 measures from the 14 tests common across three sessions: baseline (r1), one-day retest (r2), and 12-month follow-up (r3). Measures were grouped into five cognitive domains: Executive Function (EF), Episodic Memory (EM), Lexical/Story processing (LS), Processing Speed (PS), and Speech Fluency (SF). Baseline-referenced z-scores were computed for each domain at each time point. Retest learning (r2) and 12-month outcomes (r3) were operationalized as residual scores after regression on baseline (r1) performance.
Results: Longitudinal stability across domains was high (r1 vs. r3 correlations: $r = 0.71$ to 0.89). Figure 1 shows retest learning effects for each domain along with 12-month retention patterns. Figure 2 shows that r2 learning predicted 12-month outcomes across all five domains ($r = .40$–.47, all $p < .001$). These learning effects were domain-specific; cross-domain correlations were small and inconsistent with a generalized motivation effect. Demographic factors (age, education, vocabulary, etc.) explained little variance in learning residuals (LASSO $R^2 = .03$–.16). Among participants showing the greatest performance declines at 12 months (bottom 5% in each domain), 14-31% also showed poor r2 retest learning in the same domain—2.8-6.2× higher than expected under independence.
Conclusion: Quantifying retest learning may improve the sensitivity of longitudinal cognitive assessment. We found that retest learning predicted 12-month cognitive outcomes in each domain, suggesting that impaired learning efficiency may serve as an early marker of future cognitive decline.

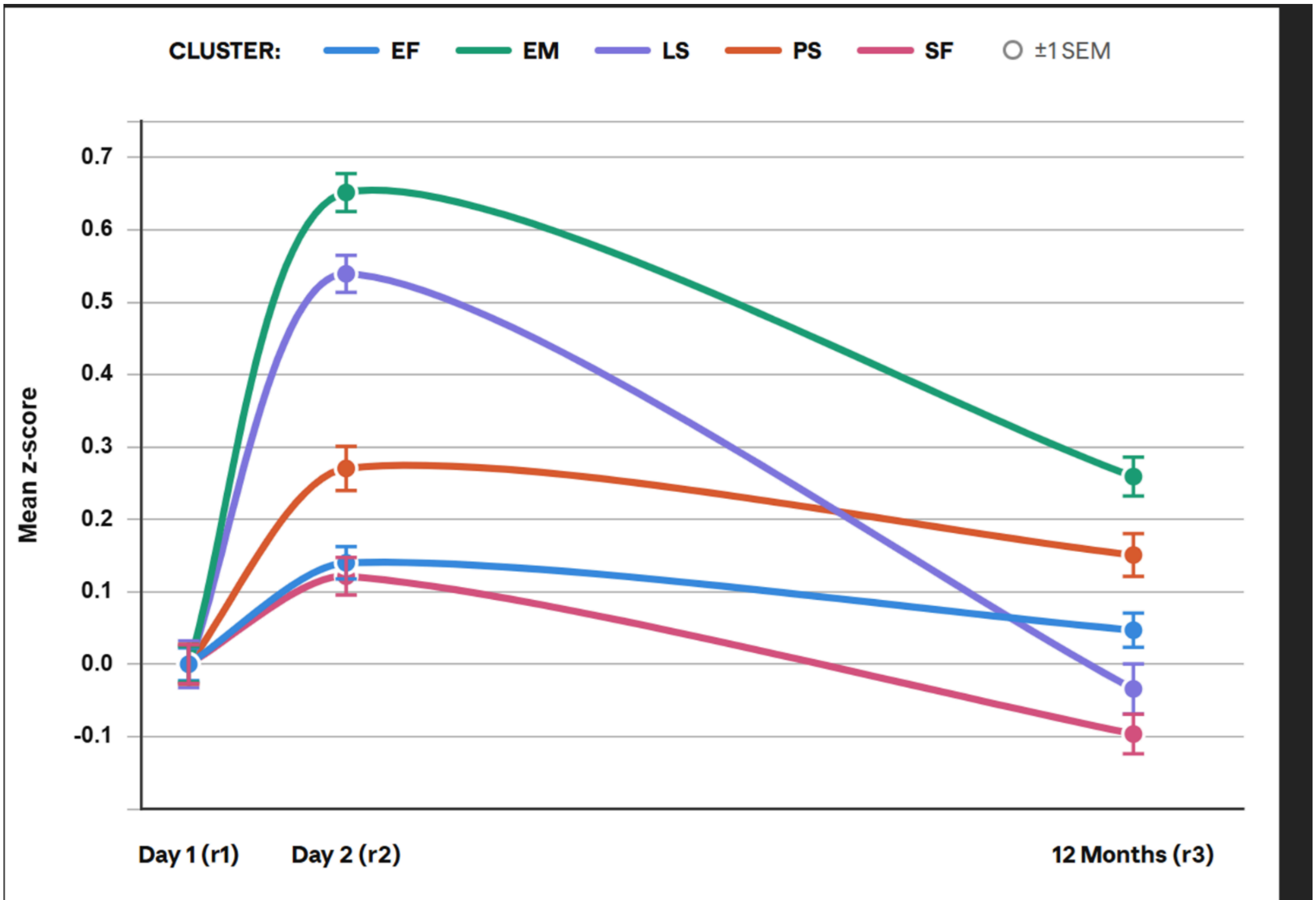

Figure 1. Retest learning and 12-month retention across cognitive domains. Mean domain z-scores (± SEM) are shown for one-day retest (Day 2) and 12-month follow-up relative to baseline. Scores were averaged within domain clusters (8–15 measures each). Episodic memory and lexical/story processing show the largest retest learning effects, while PS showed the strongest retention at 12 months. Legend: EF: Executive Function, EM: Episodic Memory, LS: Lexical/Story, PS: Processing Speed, SF: Speech fluency.

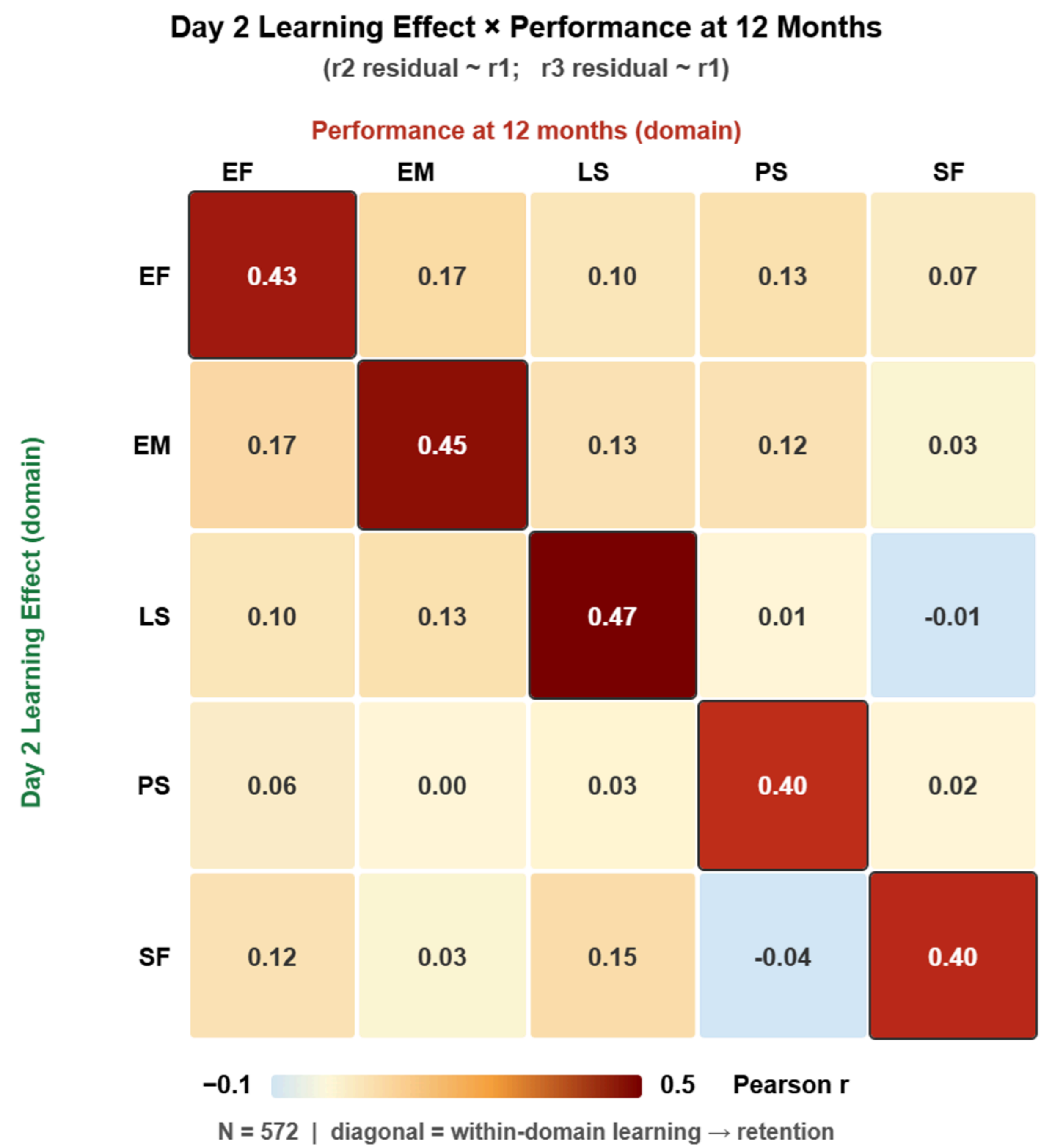

Figure 2. Correlation matrix showing the relationship between learning effects for each domain at day 2 and domain outcome scores at 12 months (regressed for performance at r1). Diagonal cells reflect within-domain learning-to-retention correlations (r = .40–.47) See Figure 1 for abbreviations.