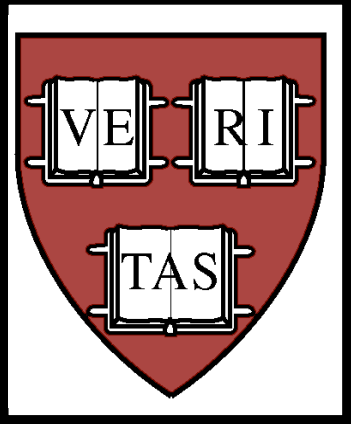




Within-Individual Precision Measurement of Cognitive Performance in Older Adults Using Ambulatory Burst Sampling

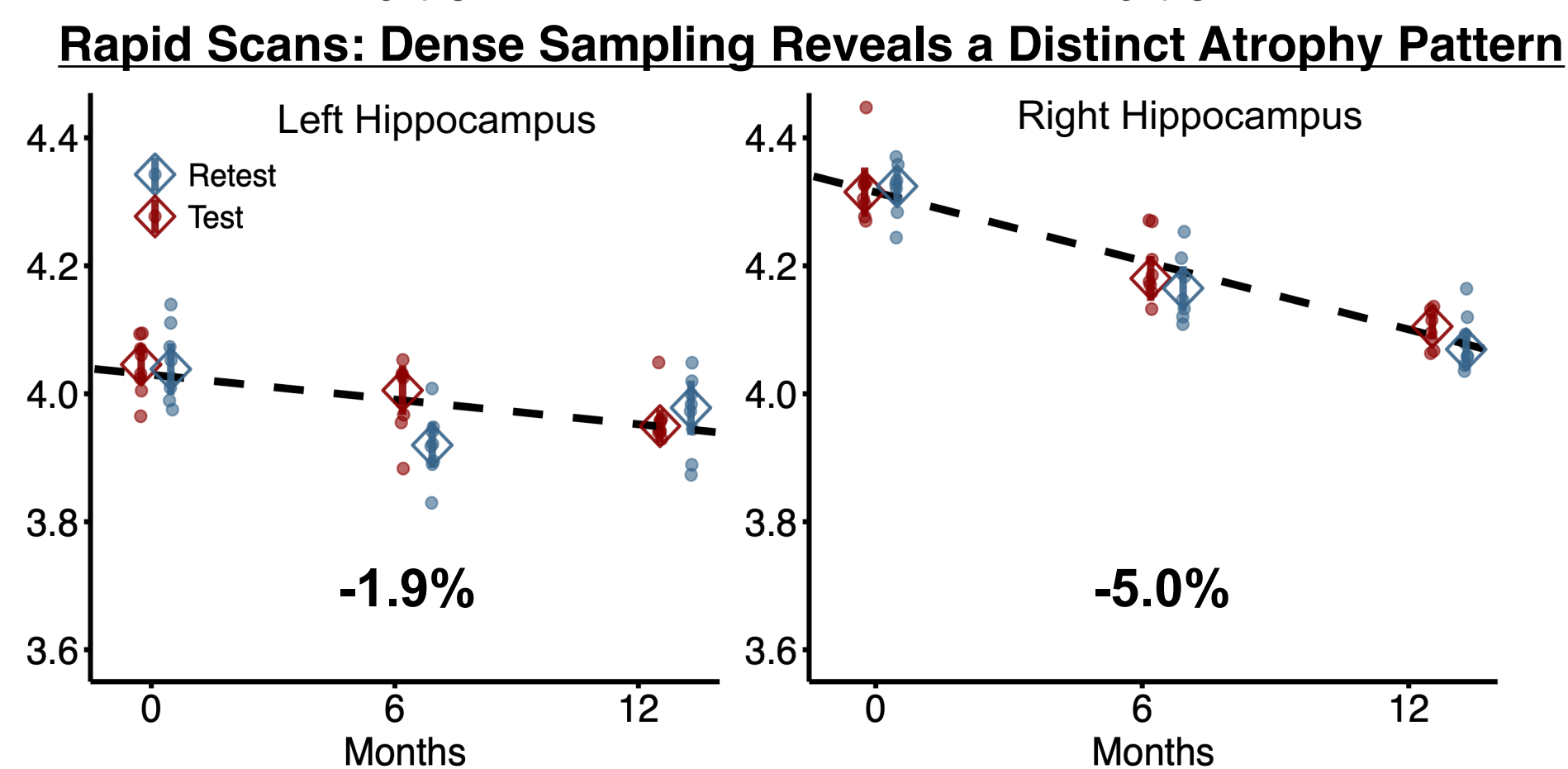
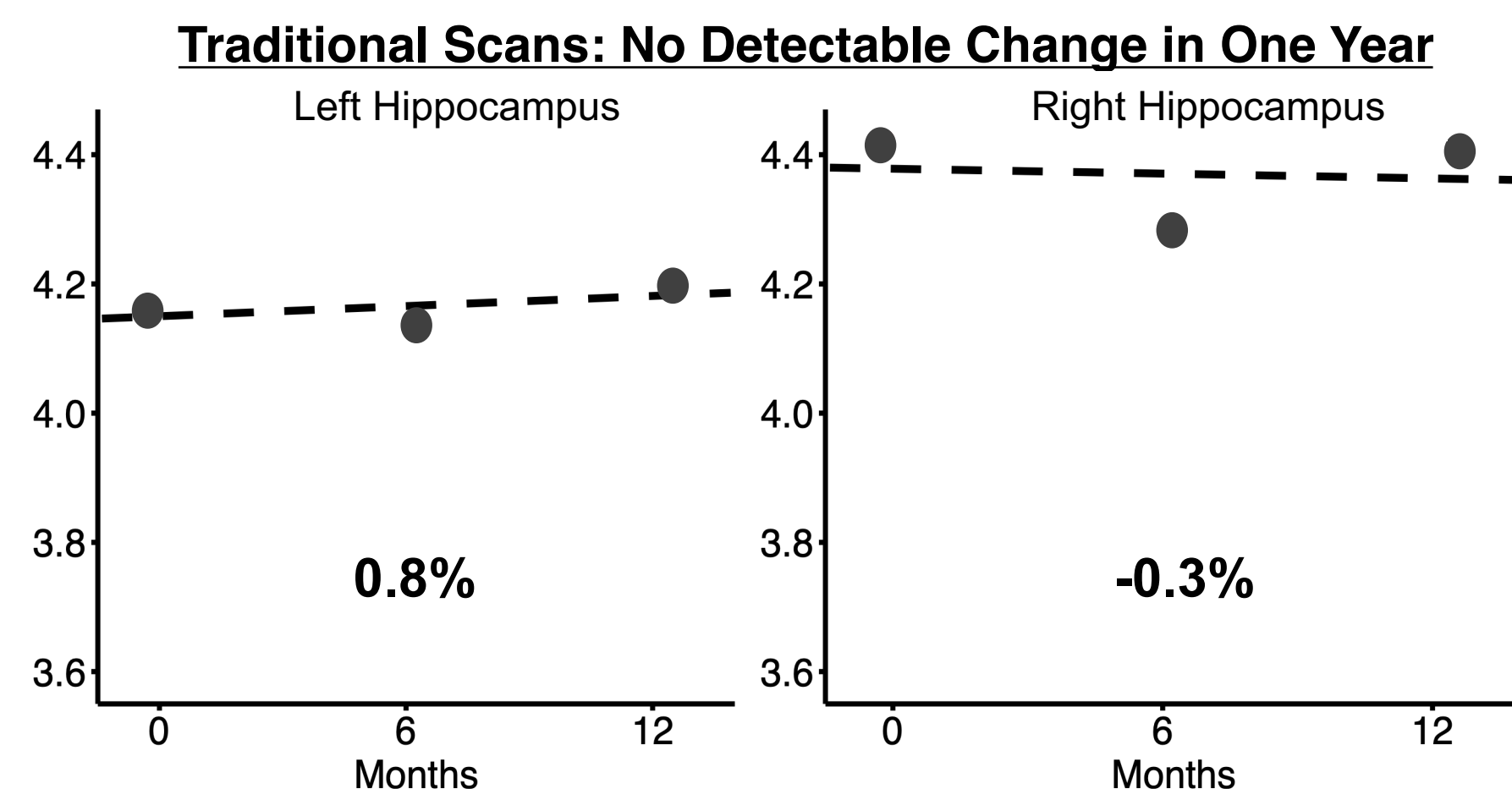


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Introduction

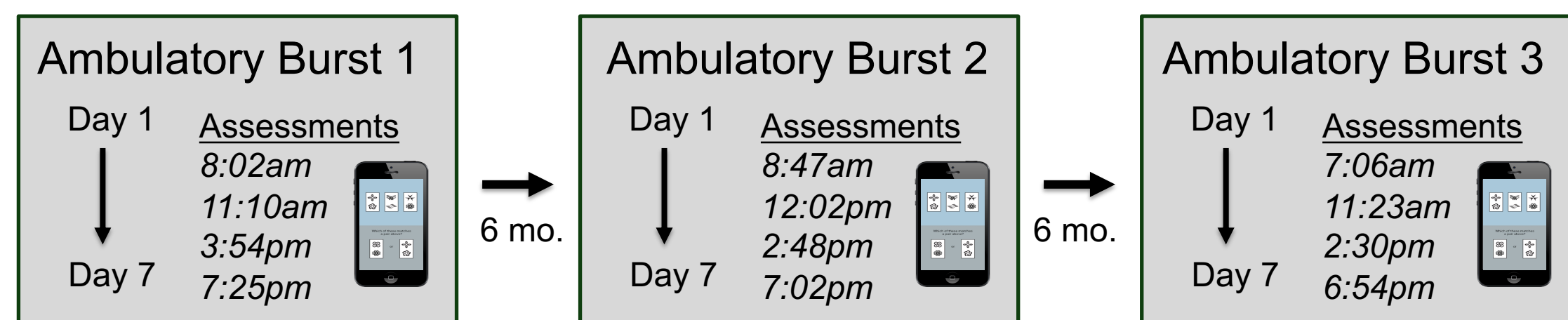
- Detecting cognitive change within individuals over short intervals remains a major challenge in aging research.
- Advances in MRI scanning demonstrate how dense sampling boosts precision to reveal subtle changes masked by traditional single scans.¹²
- Single-session cognitive testing is hampered by practice effects and state fluctuations, limiting sensitivity to within-person changes.
- High-frequency mobile testing enables dense behavioral sampling, yielding robust individual performance estimates.³

Proof of Concept: Rapid Structural Scans

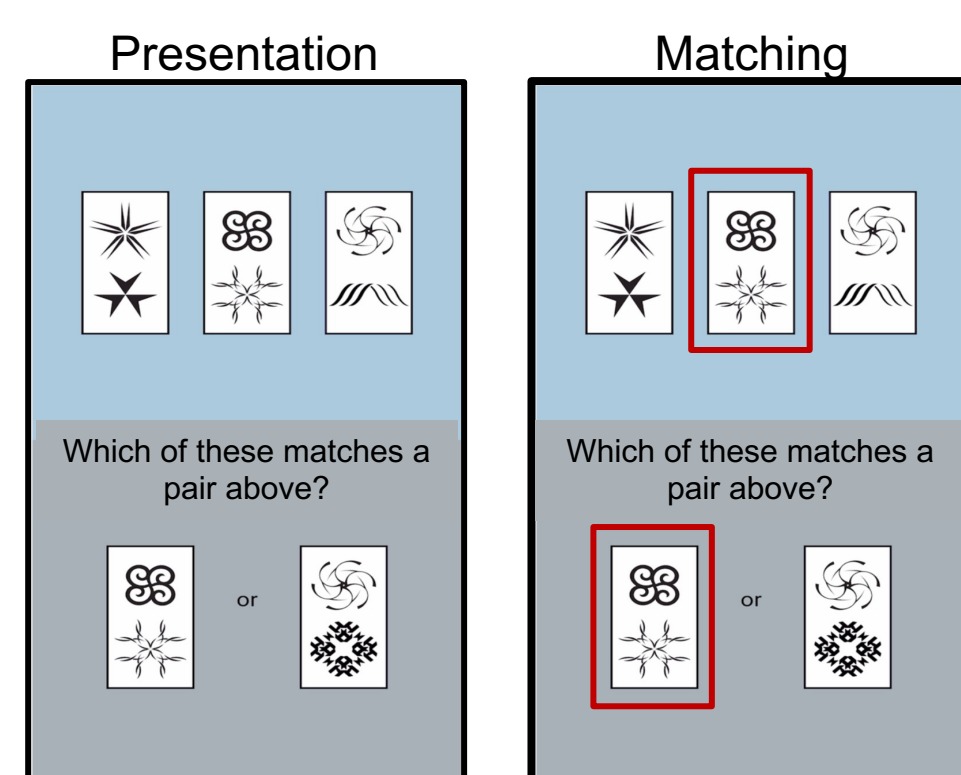


Data from a single 70-year-old male over one year. Top: one standard ADNI scan (312 sec) per session yields no detectable hippocampal change. Bottom: accelerated acquisition (72 sec) enables 8 rapid scans across two independent sessions (test: red; retest: blue), directly quantifying measurement error and revealing asymmetrical atrophy obscured by traditional scanning.

Methods: Dense Sampling of Cognition

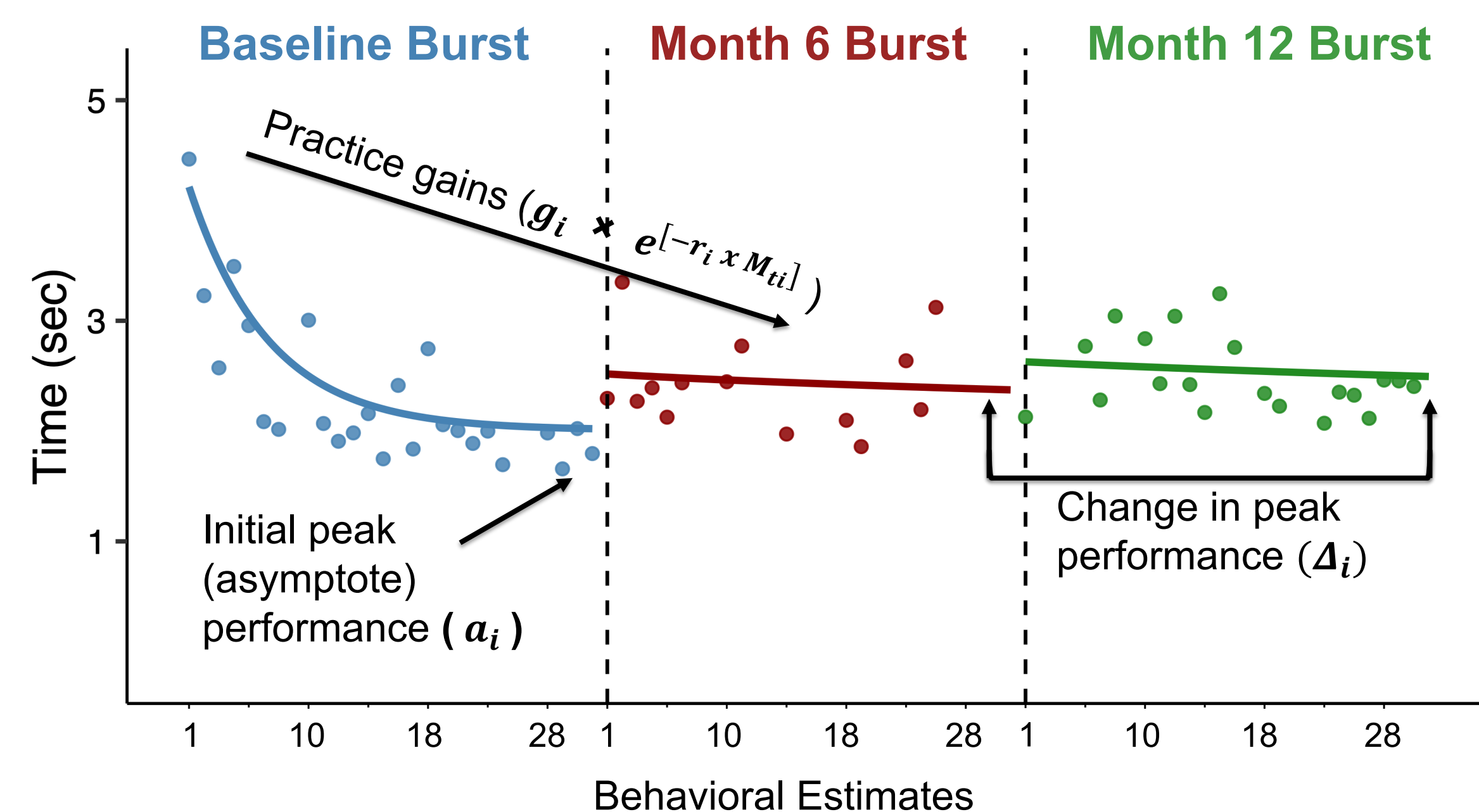


Forty cognitively unimpaired older adults (mean age 69.5 years, range 57–82; 24 female) completed smartphone-based cognitive testing via the M2C2 platform.⁴ Using a measurement-burst design,⁵ participants completed four daily sessions (5–10 min each) for seven consecutive days, with bursts repeated at six-month intervals. Compliance was high, with participants completing a mean of 86.2% of scheduled assessments (median 89%, range 32–100%).



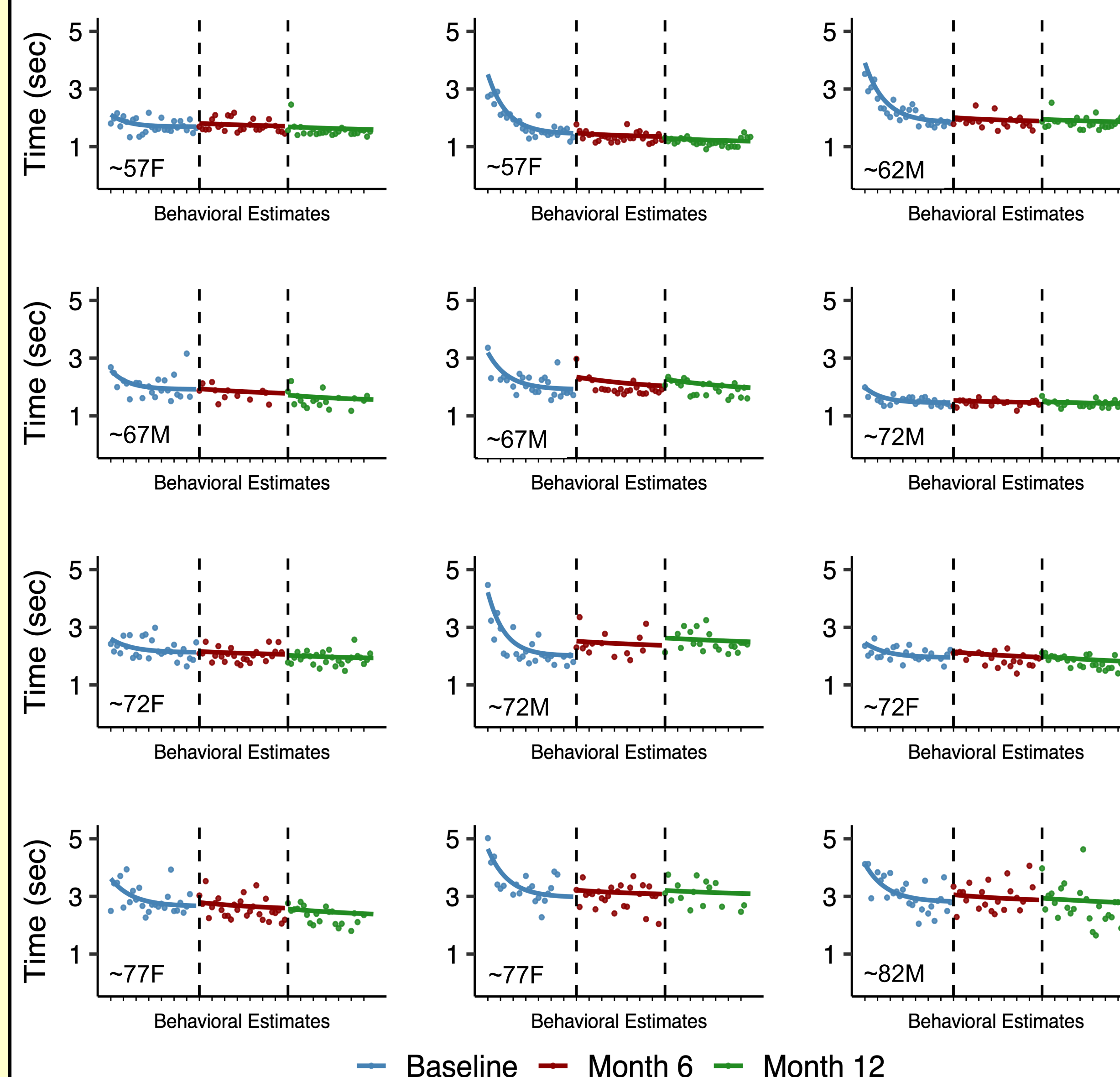
Symbol Search Task: Participants matched symbol pairs across 20 trials per session as quickly and as accurately as possible. Median response time (ms) was the primary outcome; accuracy was near ceiling (>90% correct).

The Asymptote Captures True Ability and Change



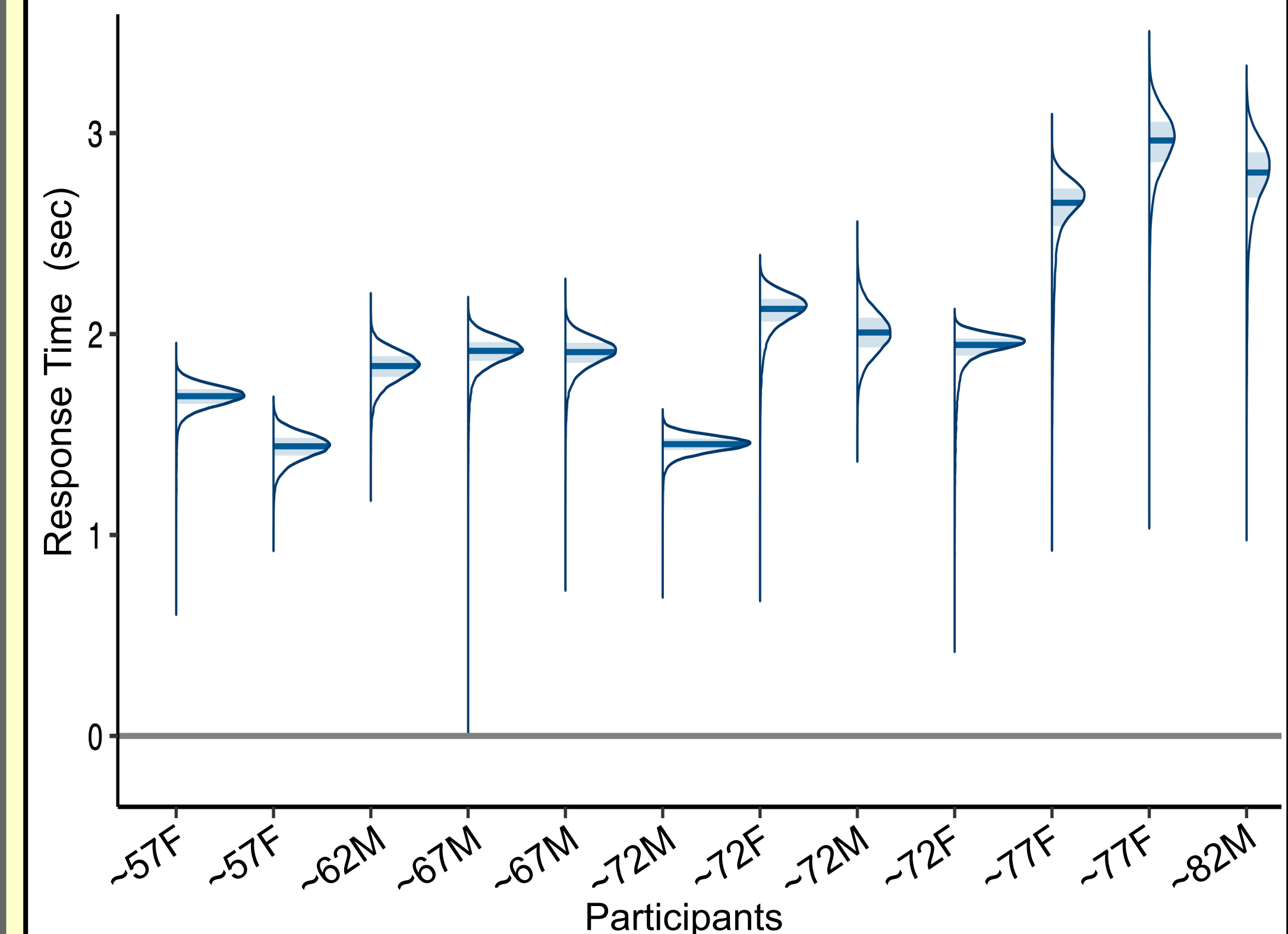
A double-exponential model⁶ captures rapid within-burst learning and slower across-burst change. Practice effects are modeled explicitly (g, g^*, r, r^*), isolating the **asymptote** (a , peak performance) and its change across bursts (Δ) as the cleaner signal of cognitive change.

Symbol Search Performance Is Stable Across One Year



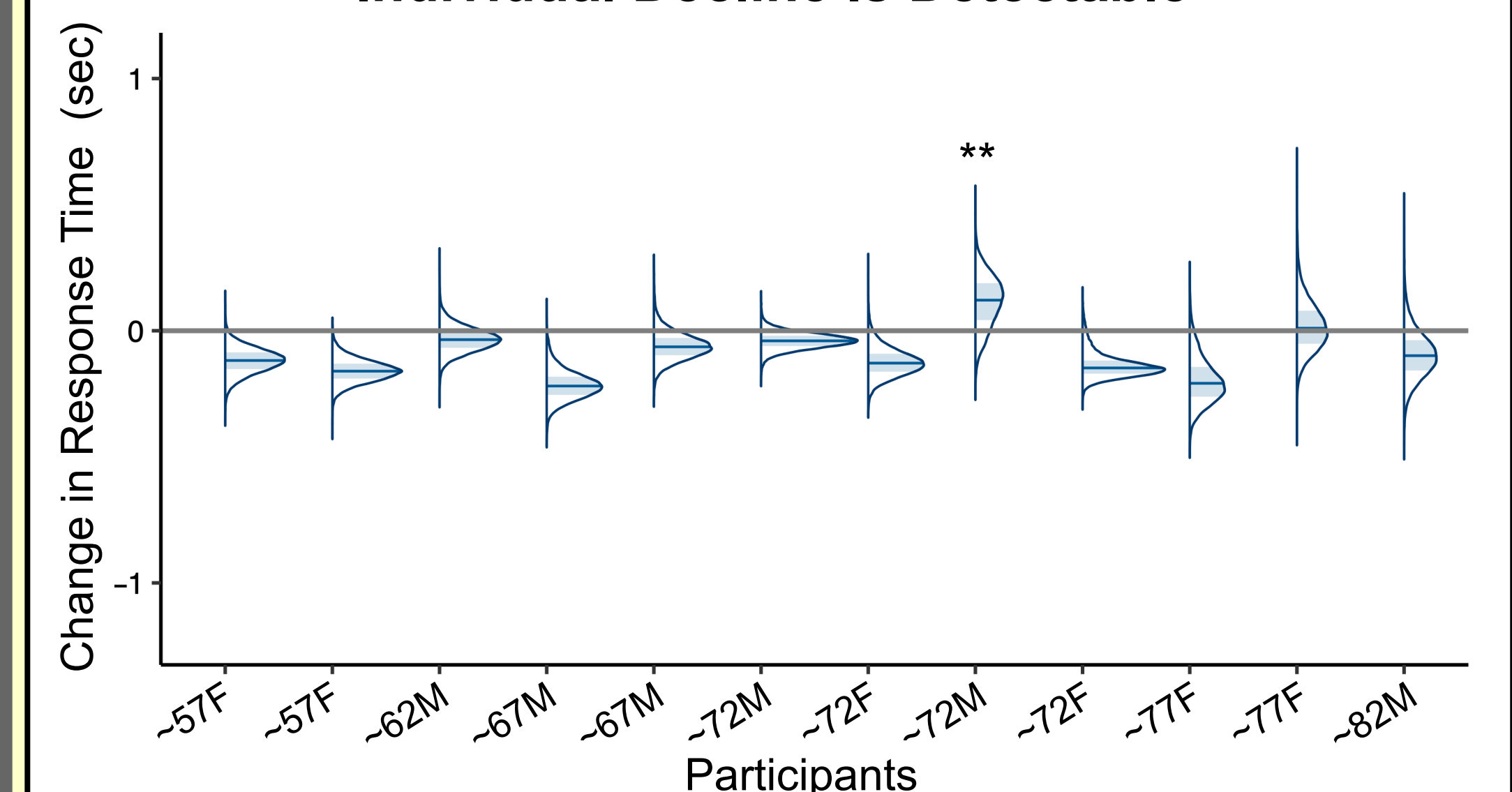
Learning curves for 12 participants (ages reflect median of 5-year bins) across three measurement bursts. Within each burst, response times decline rapidly as participants acquire task familiarity. Once practice effects stabilize, asymptotic performance remains consistent across bursts and over the 12-month study period. Substantial individual differences are apparent in learning rate and asymptotic speed, with older participants showing slower asymptotes and greater within-burst variability.

Asymptote Captures Age-Related Processing Speed



Asymptotic performance estimates, ordered by participant age, reveal a clear gradient in Symbol Search processing speed across the age range (57–82 years; ages reflect median of 5-year bins). Dark bands show posterior medians; shading shows 80% credible intervals. Age-related slowing was confirmed in the full baseline cohort ($n=40$; $r=0.48$, $p=0.002$).

Individual Decline Is Detectable



Change in asymptotic response time over one year, ordered by age. Posterior distributions cluster slightly below zero indicating stable performance with modest residual practice effects. One older participant (~72M) shows a credible positive shift, indicating detectable slowing.

Conclusions

High-frequency, dense sampling yields stable, precise estimates of individual processing speed in older adults. The Bayesian double-exponential model isolates asymptotic performance from learning, capturing meaningful age-related differences that remain stable across one year. Critically, individual-level cognitive decline is detectable, which demonstrates the potential sensitivity of dense sampling via smartphones for within-person monitoring of cognitive aging.

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