Influence of serial subtraction tasks on transient characteristics of postural control

Cody A. Reed, Camryn K. DuBois, Keith A. Hutchison, Theodore J. Huppert, Scott M. Monfort

Influence of Serial Subtraction Tasks on Transient Characteristics of Postural Control

Cody A. Reed[a,b], Camryn DuBois[a], Keith A. Hutchison[c], Theodore J. Huppert[d], Scott M. Monfort[a]

[a] Department of Mechanical and Industrial Engineering, Montana State University, Bozeman, Montana, USA

[b] Sanford Orthopedics & Sports Medicine Research, Sanford Health, Sioux Falls, South Dakota, USA

[c] Department of Psychology, Montana State University, Bozeman, Montana, USA

[d] Department of Department of Electrical and Computer Engineering, University of Pittsburgh, Pittsburgh, Pennsylvania, USA

Corresponding Author: Scott M. Monfort **Address:** P.O. Box 173800, Bozeman, Montana 59717-3800, USA. **Email:** scott.monfort@montana.edu **Phone:** +1 406 994 6294

Declaration of Interest

This study was supported by a Montana State University Faculty Excellence Grant. The funding source did not have any involvement in the study design, data collection, or data analysis/interpretation. This research did not receive any other specific grant from funding agencies in the public, commercial, or not-for-profit sectors. The authors have no other interests to disclose.

Abstract

We sought to better understand the influence of cognitive perturbations on transient aspects of postural control. Twenty healthy, younger adults had their postural control assessed during eyes open quiet stance. Participants completed three different conditions that either had no cognitive perturbation present, an easy cognitive perturbation (i.e., serial subtraction by ones), or a more difficult cognitive perturbation (i.e., serial subtraction by sevens). All trials finished with 60 seconds of undisturbed eyes open quiet stance, which was the focus of the balance assessment. 95% confidence ellipse area (EA) was calculated for 5-second epochs throughout the trial. The difference in EA from the first epoch after participants started (onset) or stopped (offset) the cognitive task to the last epoch of the trial (i.e., 55-60 seconds after perturbation) was used to characterize transient postural control behavior. Functional near-infrared spectroscopy was also used to quantify changes in prefrontal cortex activation during the counting tasks to support interpretation of the transient balance findings. There was a significant effect of condition for transient balance characteristics following a cognitive perturbation ($P < 0.001$), with greater transient increases in postural sway for both difficult (Cohen's d = 0.40, $P < 0.001$) and easier (Cohen's d = 0.29, $P = 0.013$) cognitive perturbations relative to no cognitive perturbation. The onset of cognitive tasks was also associated with greater transient increases in postural sway than the offset of the cognitive tasks (Cohen's d = 0.24, $P = 0.019$). The functional near-infrared spectroscopy data indicated that a significant decrease in deoxygenated hemoglobin was observed for left Brodmann area 46 for both the subtraction by ones (T = -3.97; Benjamini-Hochberg significance value (q) = 0.008) and subtraction by sevens (T = -3.11; q = 0.036) conditions relative to the baseline condition. The subtraction by sevens condition was also associated with a relative increase in deoxygenated hemoglobin for the right Brodmann area 9 (T

= 3.36; q = 0.026) compared to the subtraction by ones condition. In conclusion, serial subtraction can elicit transient increases in postural sway, with more difficult tasks and the onset of the cognitive-motor challenge exhibiting magnified effects. Additionally, even the cessation of a cognitive task (i.e., serial subtraction) can be associated with lingering perturbing effects on balance control.

1. Introduction

Although postural control is often thought of as a simple task, it requires the integration of sensory systems, motor control, and attentional resources to maintain balance (Horak, 2006; Massion, 1994). Postural control is often measured using parameters that characterize the movement of the center of pressure (CoP) trajectory over the course of a trial due to their clinical significance (Maki, Holliday, & Topper, 1994; Piirtola & Era, 2006). Traditionally, these CoP parameters are represented as whole-trial estimates (Carpenter, Frank, Winter, & Peysar, 2001; Maki, et al., 1994; Thomas E. Prieto, Myklebust, Hoffmann, Lovett, & Myklebust, 1996; van der Kooij, Campbell, & Carpenter, 2011), with longer duration trials (1-2 minutes) thought to improve the reliability of the whole-trial estimates (Carpenter, et al., 2001; Doyle, Hsiao-Wecksler, Ragan, & Rosengren, 2007; Lafond, Corriveau, Hébert, & Prince, 2004).

Although longer trials improve whole-trial estimate reliability, recent research suggests that this approach masks unique and potentially clinically-relevant transient behavior (i.e., a period of increased sway followed by a transition to a more stable, quasi-steady-state level) by marginalizing the initial transient portion of balance trials (Kozinc & Šarabon, 2021a, 2021b; Kozinc, Trajković, & Šarabon, 2021; Kozinc, Trajković, Smajla, & Šarabon, 2021; Reed, Chaudhari, Worthen-Chaudhari, Bigelow, & Monfort, 2020). Our prior work established a simple approach to quantify this transient behavior that divides balance trials into multiple epochs and calculates common postural sway variables for each epoch independently, rather than just a single estimate for a given trial. Then, the change between sway estimates for the first epoch (i.e., reflecting the initial destabilized period) and the last epoch (i.e., reflecting the quasi-steady-state period) is calculated as a measure of transient balance behavior (Reed, et al., 2020). Additionally, more complex approaches have attempted to quantify the temporal structure of

CoP fluctuations (McNevin & Wulf, 2002; Itshak Melzer, Kurz, & Oddsson, 2010; Mitra, 2003; Ramdani, Tallon, Bernard, & Blain, 2013; Riley, Baker, Schmit, & Weaver, 2005), but the clinical utility of these methods is still not fully understood. Transient features of quiet stance postural control have most often been reported following the onset of a sensory transition such as vision occlusion (Asslander & Peterka, 2014; Assländer & Peterka, 2016; Boucher, Teasdale, Courtemanche, Bard, & Fleury, 1995; Brown, et al., 2006; Carroll & Freedman, 1993; Honeine, Crisafulli, & Schieppati, 2017), which suggests that the transient behavior may be associated with sensory reweighting (i.e., changes in the relative reliance on each sensory system based on environmental conditions) (Asslander & Peterka, 2014; Nashner & Berthoz, 1978). Notably, increased postural sway has also been associated with regaining sensory information that had been acutely deprived (e.g., opening eyes after having them closed) in diabetic populations (Boucher, et al., 1995). Therefore, sensory reweighting following the removal or addition of sensory information can result in increased postural sway.

Our previous work supports the ability for the transient approach to quantify sensory reweighting by detecting transient behavior in eyes closed quiet stance, however we have also found transient behavior to a lesser degree in eyes open quiet stance (Reed, et al., 2020). Because no changes in sensory information occurred in eyes open conditions, the persistent transient behavior suggests that additional factors contribute to transient behavior beyond solely sensory reweighting. One factor that may contribute to the transient behavior in our previous eyes open condition is a perturbation that was introduced by how the trials were initiated. Specifically, participants in our prior work initiated the start of trials by counting down aloud ‘3-2-1-Go’, with participants either closing their eyes on ‘Go’ (eyes closed condition) or maintaining their gaze at a fixation cross on ‘Go’ (eyes open condition). Therefore, it is possible that a perturbation was induced by counting down (e.g., shifting focus of attention, articulation, heightened anxiety of initiating the trial, etc.) that potentially contributed to the remnant transient behavior.

We proposed that attentional demands associated with participants counting down may have contributed to the persistent transient effects previously observed in eyes open trials. A substantial body of literature suggests that human movement is attentionally-demanding (Al-Yahya, et al., 2016; Woollacott & Shumway-Cook, 2002). Performing cognitive tasks concurrently with motor task can strain attentional resources and give rise to performance deficits in either or both the cognitive and motor tasks (Cinar, Saxena, McFadyen, Lamontagne, & Gagnon, 2021; Woollacott & Shumway-Cook, 2002). These dual-task impairments (e.g., increased postural sway) are often more pronounced with more challenging motor and/or cognitive tasks and with lower functioning individuals (Woollacott & Shumway-Cook, 2002) or those with neurological (Register-Mihalik, Littleton, & Guskiewicz, 2013) or musculoskeletal impairments (Miko, et al., 2020). Others have also reported that the addition of some cognitive tasks can lead to decreased postural sway in healthy adults due to participants adopting a more automatic postural control strategy as attention is shifted to the cognitive task (Richer & Lajoie, 2020; Richer, Saunders, Polskaia, & Lajoie, 2017; St-Amant, Rahman, Polskaia, Fraser, & Lajoie, 2020). Given the previously-established ability for cognitive tasks to influence other balance control measures (Fraizer & Mitra, 2008; I. Melzer, Benjuya, & Kaplanski, 2001; Pellecchia, 2003; Shumway-Cook & Woollacott, 2000; St-Amant, et al., 2020), it is important to investigate the sensitivity of transient balance characteristics to further understand their utility in assessing postural control as well as identify confounding factors that influence their estimation. Additionally, whether cognitive tasks elicit perturbing effects at both their onset and offset, analogous to effects of adding/removing sensory information, remains unknown but can be probed using an epoch-based analysis approach. Finally, measuring brain activation alongside postural control during cognitive-motor testing paradigms can help provide more robust interpretations of the observed behavior (St-Amant, et al., 2020). Expanding on this multidisciplinary approach of using functional neuroimaging in postural control research provides an opportunity to more completely interpret data from cognitive-motor research protocols.

The overall purpose of this study was to better understand the influence of cognitive perturbations on transient postural control behavior. We hypothesized that acute cognitive perturbations would introduce transient responses in postural control compared to no cognitive perturbation, with an increased magnitude in transient effects as the cognitive perturbation task difficulty increases. We also expected increased CoP sway to be present at both the onset and offset of cognitive tasks, but to be more pronounced during the onset period.

2. Methods

2.1. Participants

Young adults (18-30 years old) were recruited from Montana State University and the Bozeman, MT community. Individuals were excluded if they had a known neurological impairment, a lower-extremity surgery within ten years prior to testing, a concussion within one year prior to testing, or a lower extremity injury within three months prior to testing. Twenty individuals (22.4 ± 2.1 years, 72.2 ± 10.7 kg, 1.80 ± 0.15 m, 13 males/7 females) participated in the study (see Section 2.4 for power analysis description).

2.2. Protocol

Prior to testing, Institutional Review Board-approved written informed consent was obtained from all participants. Participants then completed a testing session that analyzed their postural control and brain activation during eyes open stance, which included various cognitive perturbations. All tests were performed during a single visit.

Each testing session consisted of standing balance under three conditions, which corresponded to different difficulty levels of the cognitive perturbation (i.e., NO, LO, and HI). The NO condition was a control and involved no cognitive perturbation throughout the trial. The LO condition involved counting aloud backward by 1s from a random 3-digit number, whereas the HI condition involved counting aloud backward by 7s from a random 3-digit number. These cognitive perturbations were chosen because serial subtraction tasks have frequently been used for dual-tasking (Andersson, Hagman, Talianzadeh, Svedberg, & Larsen, 2002; Hauer, et al., 2003; Honeine, et al., 2017; Pellecchia, 2003), and they are the most analogous to the ‘3-2-1-Go’ countdown procedure from our previous work that observed persistent transient behavior during eyes open stance (Reed, et al., 2020). For each condition, participants completed three successful 100-second trials, resulting in a total of 9 trials.

Each 100-second trial consisted of three phases (0-30 seconds: Baseline, 30-40 seconds: Stimulus, 40-100 seconds: Testing) (**Figure 1**). During the Baseline phase, participants began the trial and performed quiet, eyes open stance. The Baseline phase was necessary to provide pre-stimulus baseline for balance performance and to calibrate a functional near-infrared spectroscopy (fNIRS) device that was simultaneously collecting data on hemodynamic changes in the prefrontal cortex (described further in Section 2.3.2). During the Stimulus phase, participants completed a cognitive task while maintaining eyes open stance. During the Testing phase, participants stopped performing the cognitive task and exclusively maintained quiet, eyes open stance until the end of the trial. While the Baseline and Testing phases were identical across all conditions, the task performed during the Stimulus phase varied by condition (i.e., NO, LO, or HI – see **Figure 1**). The subtraction tasks for the LO and HI conditions were initiated when a researcher said a randomly-selected 3-digit number that participants then used as the starting point for the serial subtraction tasks. For all conditions, the Stimulus phase transitioned immediately into the Testing phase when a researcher said ‘Go’ 40 seconds after the start of the trial (**Figure 1**). This cue reminded the participants to stop performing the cognitive task (i.e., counting backwards aloud) and remain as still as possible during eyes open stance until the end of the trial. Notably, this was the exact same cue for all conditions, which was selected to enable direct comparisons across the baseline (NO) condition compared to the two cognitive conditions (LO and HI).

For all trials, participants stood without shoes and positioned the medial borders of their feet 5 cm apart (Monfort, et al., 2016; Reed, et al., 2020). Participants were instructed to stand as still as possible throughout the entirety of the 100-second trials with their arms relaxed at their sides, while focusing their gaze on a target (fixation cross, 10 cm x 10 cm) placed 2 m away and 1.69 m high. After participants confirmed they were in position and ready, the researcher counted down ‘3-2-1-Begin’ to initiate the start of the 100-second trial (**Figure 1**). Prior to the first recorded trial in every condition, participants performed an abbreviated practice trial in which researchers confirmed that the participant understood the instructions, verbal cues, and cognitive dual-task. Between trials, participants were allowed a self-selected amount of rest. Any trial where a participant did not comply with experimental protocol was omitted and an additional successful trial was then performed to obtain three successful trials in each condition

(9 total, successful trials). The testing order of the conditions was block-randomized for every participant. Participants took a mandatory break of at least 2 minutes between conditions.

2.3. Data Processing

2.3.1. Postural Control

During each trial, CoP data were recorded at 1000 Hz using a balance plate (BP5046; Bertec Corp.; Columbus, OH) and captured using a custom data collection program written in LabVIEW (National Instruments; Austin, TX). Using custom MATLAB scripts (version 2018b; MathWorks Inc.; Natick, MA), the data were 4th order Butterworth lowpass filtered at 20 Hz (T. E. Prieto, Myklebust, & Myklebust, 1993; Reed, et al., 2020), demeaned using epoch-specific mean values, and 95% confidence ellipse area (EA) was calculated for 5-second epochs throughout the 100-second trial.

Transient behavior of EA was quantified by calculating the difference in epoch estimates (i.e., ΔEA) for the onset and offset of the cognitive stimuli. Specifically, ΔEA for the stimulus onset was calculated as the difference between the first epoch of the Stimulus phase (i.e., first five seconds following start of cognitive task) and the last epoch of the Testing phase (i.e., representing quasi-steady state balance). The ΔEA for the offset of the stimulus was calculated as the difference between the first and the last epochs of the Testing phase. Note that the offset ΔEA is analogous to the DIF_ovr metric from our previous study (Reed, et al., 2020). The EA CoP parameter was specifically chosen based on its reported clinical relevance in assessing fall risk (I. Melzer, Benjuya, & Kaplanski, 2004; Sample, et al., 2016; Thapa, Gideon, Brockman, Fought, & Ray, 1996). Additionally, in our previous work, the ΔEA variable demonstrated superior ability to distinguish between eyes closed and eyes open stance, and between young and older adults (Reed, et al., 2020). We therefore focused our analysis on ΔEA because the results of our prior work highlighted the enhanced discriminative ability of ΔEA compared to CoP parameters of mean velocity or root-mean-square displacement. Additionally, we sought to limit Type I statistical error as traditional CoP parameters are often highly correlated with each other (Goldie, Bach, & Evans, 1989).

2.3.2. Prefrontal Cortex Activation

fNIRS data were collected to verify the impact of the cognitive conditions on prefrontal cortex (PFC) activation. The PFC was selected because of its well-established link to executive functioning and prior investigation during dual-task postural control and gait (Gupta & Tranel, 2012; St-Amant, et al., 2020; Wittenberg, Thompson, Nam, & Franz, 2017; Yogev-Seligmann, Hausdorff, & Giladi, 2008).

An 8-source, 8-detector fNIRS system (NIRSport 1, NIRx Medical Technologies, USA) was used with 128-position pre-labeled caps in a 10-5 layout (EasyCap GmbH, Germany). A standard 8x8 PFC montage with short-separation channels available through NIRx was used to guide optode placement based on 10-20 EEG landmarks (see **Supplemental Material**). The montage consists of 8 sources, 7 detectors for standard-distance channels (i.e., 3 cm), and one detector that was used to provide 8 short-separation channels (i.e., one for each source optode, each separated at 8 mm) via multiplexing with a NIRx short-distance detector bundle. Cap placement was standardized using participants head circumference to obtain the proper cap size, and midpoints of nasion-inion and right/left pre-auricular points to consistently position the cap to ensure Cz was located centrally on the top of the head. The optode positions were later registered to a Talairach Daemon atlas to enable region of interest (ROI) analysis (Lancaster, et al., 2000; Zhai, Santosa, & Huppert, 2020). Each fNIRS channel was measured at 7.8125 Hz at wavelengths of 760 nm and 850 nm and used to estimate changes in oxygenated (HbO) and deoxygenated (Hbr) blood concentration using the modified Beer-Lambert law (Kocsis, Herman, & Eke, 2006). The cap chin strap was not secured to mitigate the potential for jaw movements during verbal responses to introduce artifacts into the fNIRS signals (Menant, et al., 2020).

fNIRS data processing and statistical analysis were completed using the NIRS Toolbox (GitHub commit: 4ef1901) (Hendrik Santosa, Zhai, Fishburn, & Huppert, 2018) in MATLAB (version 2019a). The data were visually inspected for any obvious motion-related artifacts in the fNIRS signal (large spikes or shifts of the data). Only 1 of the 180 trials was identified as a substantial artifact and removed from analysis. All other potential motion artifacts were dealt with in our statistical model using robust (iterative outlier down-weighting) statistical methods. Trials with saturated channels were addressed using the ‘FixNaNs’ module in the NIRS Toolbox (Hendrik Santosa, et al., 2018). The data were then down sampled to 4 Hz to reduce computational demands while retaining sufficiently high sampling rate relative to the multi-second timescale of typical hemodynamic responses (Cui, Bray, & Reiss, 2010; Kontos, et al., 2014; Menant, et al., 2020). Each 100-second trial was trimmed to 20 seconds of baseline before the onset of the stimulus, the 10 second stimulus, and 25 seconds of baseline following the conclusion of the stimulus. Raw data were converted to HbO and Hbr relative to baseline using the modified Beer-Lambert relation with partial pathlength factor of 0.1 (Jacques, 2013). Subject-level statistics were calculated using an autoregressive iterative robust least squares (AR-IRLS) general linear model assuming a canonical hemodynamic response function and including the 8 short-separation channels as regressors (Barker, Aarabi, & Huppert, 2013). In brief, this algorithm uses an autoregressive model to correct for serial correlation of the noise due to physiological oscillations. These correlations are known to cause strong false-positives and uncontrolled type I error (e.g. inaccurate statistical probabilities) if uncorrected. In addition, this model also performs a robust statistical regression using a bisquare weighting to reduce the leverage of statistical outliers (e.g. any remaining motion artifacts). This approach has demonstrated superior ability to correct for systemic physiological signal artifacts compared to alternative approaches (H. Santosa, Zhai, Fishburn, Sparto, & Huppert, 2020). After running the first-level statistical model, subject-level outliers were then removed using the NIRS Toolbox ‘RemoveOutlierSubjects’ function, which removes subjects that have statistically above norm leverage on the group level mixed-effects model ($p<0.05$ threshold based on the Z-transformed distribution of Mahalanobis distance leverage). One participant was removed in this step. Group level analyses were then performed to obtain HbO and Hbr beta (β) values using a robust mixed effects model with ‘Subject’ as a random effect and ‘Condition’ as a fixed effect. In this algorithm, the first level statistical noise estimates were used to pre-whiten the group-level model (Hendrik Santosa, et al., 2018). This algorithm also provides robust outlier down-weighting. The region of interest estimates for bilateral Brodmann areas (BA) 9, 10, and 46 were computed based on the location of the fNIRS measurements relative to the Talairach Daemon atlas (Zhai, et al., 2020). This region-of-interest model is based on a projection of the underlying ROI definitions in the brain space through the fNIRS measurement model to produce a testable hypothesis of the expected spatial pattern of activity in measurement (channel) space. This enables testing the null hypothesis that the measured brain activity is inconsistent with this underlying ROI. As a null hypothesis, this approach is unable to confirm activity of this ROI compared to a competing hypothesis (e.g. an alternative neighboring or overlapping ROI). Thus, our selection of BA 9, 10, and 46 for this test is based on our prior expectations of regions associated with the cognitive task. Finally, statistical T-test contrasts of β values for HbO and Hbr were assessed and the Benjamini-Hochberg significance values (q) were computed and reported to correct for multiple comparisons. Increased activation was defined by either an increase in HbO or a decrease in Hbr, as has previously been reported (Scholkmann, et al., 2014).

2.4. Power Analysis

An *a priori* power analysis was conducted using General Linear Mixed Model Power and Sample Size (GLIMMPSE) software version 3.0 (Kreidler, et al., 2013). Power was calculated for a Condition main effect using the Hotelling-Lawley trace test. The dependent variable was ΔEA, and we used predicted values of 0 mm^2, 39.3 mm^2, and 94.6 mm^2 for NO, LO, and HI conditions, respectively (Reed, et al., 2020). These values were based on the hypothesized graduated effect of cognitive task difficulty (i.e., more challenging tasks would perturb balance to a greater extent). We assumed our previous eyes open condition with a ‘3-2-1-Go’ countdown would be similar to the LO condition and the challenging cognitive task would more closely reflect an eyes closed perturbation (Reed, et al., 2020). Standard deviations and correlations between conditions were similarly based on previously reported data (Reed, et al., 2020). A sample size of 19 participants was determined to provide 82.6% statistical power to detect a main effect of Condition for a significance level of $\alpha = 0.05$.

2.5. Statistical Analysis

A mixed effects model was used to test for differences in the transient characteristic ΔEA between NO, LO, and HI conditions. ‘Participant’ was included as a random effect. ‘Condition’

(NO, LO, HI), ‘Stimulus Event’ (onset, offset), ‘Trial Number’ (1, 2, 3), and ‘Condition*Stimulus Event’ were considered as fixed effects. Tests were run on both the raw scale ΔEA and ΔEA calculated after taking the natural logarithm of epoch estimates because the raw scale model residuals exhibited some deviation from normality. Model fits were superior (based on AICc, BIC, and normality of model residuals) for the natural logarithm data, without the interaction term, and when using average estimates for the three trials rather than having individual trial estimates with a ‘Trial Number’ fixed factor. As a result, statistics for the average natural logarithm data are presented and discussed here, with statistics for raw-scale estimates provided in Supplemental Material. Significance for all analyses was defined *a priori* at $\alpha = 0.05$.

Given that the *a priori* power analysis involved best estimates for the anticipated conditions (e.g., eyes closed and challenging cognitive tasks having similar effects), a post-hoc power analysis was done to corroborate its validity. The actual data and statistical model used to test the hypotheses in this study were used in the GLIMMPSE software to estimate achieved statistical power for the n=20 participants actually enrolled (Kreidler, et al., 2013). The results indicated that the dataset and statistical approach had 84.4% and 91.5% statistical power to detect main effects of ‘Condition’ and ‘Stimulus Event’, respectively, for $\alpha = 0.05$.

An additional check to verify the Baseline portion of the trials was similar across conditions was also conducted using a separate mixed effects model. ‘Participant’ was a random effect and ‘Condition’ was a fixed factor. The dependent variable was the natural logarithm of the average of epoch estimates for the six epochs during the Baseline portion of the trial (i.e., the first 30-seconds of the trial). All statistical analyses were performed in Minitab (version 20.3; Minitab Inc., State College, PA).

3. Results

Participants completed both the LO and HI cognitive tasks with >90% accuracy, on average (**Table 1**). A detectable decrease in both the number (*P* < 0.001) and accuracy (*P* = 0.039) of participant responses was observed for the HI condition compared to the LO condition.

The full 180 anticipated trials (20 participants x 3 conditions x 3 trials per condition) were analyzed for postural control results. The 'Condition' factor was significant for ΔEA **(Table 2**). Post-hoc analysis revealed that the HI condition was significantly different from the NO condition (**Table 3**). The LO condition exhibited a small significant difference from the NO condition (**Table 3**). The HI and LO conditions were not significantly different from each other. The 'Stimulus Event' main effect was also significant. Post-hoc analysis indicated that the onset event was associated with greater ΔEA than the offset event (Cohen's d = 0.24; *P* = 0.019). Additionally, when comparing candidate statistical models, the 'Condition* Stimulus Event' interaction was not significant (*P* = 0.581 for the Δln(EA) outcome variable). The Baseline portion of the trials were not significantly different in EA estimates between conditions (*P* = 0.79).

Unexpected greater variability in the 90-95 second epoch appeared to be largely driven by a single participant (**Figure 2**). Follow-up analyses excluding the outlier participant were conducted to determine how influential the outlier was; however, the results of these analyses remained consistent with our original analysis (see **Supplemental Tables 4 and 5**). Therefore, because we have no reason to believe that the outlier participant's data are physiologically invalid, we kept the full dataset as the basis for our analyses.

Out of the anticipated 180 fNIRS trials (20 participants x 3 conditions x 3 trials), 179 trials were included in the analysis after quality controlling the fNIRS data for large artifacts.

During data processing, data from one participant were removed by the ‘RemoveOutlierSubjects’ function, leaving a final dataset of 170 (94%) out of the 180 anticipated trials. The fNIRS data indicated that a significant decrease in Hbr was observed for left BA 46 for both the LO (β = -2.88; T = -3.97; q = 0.008) and HI (β = -2.20; T = -3.11; q = 0.036) conditions relative to the NO condition. The HI condition was also associated with a relative increase in Hbr for the right BA 9 (β = 2.70; T = 3.36; q = 0.026) compared to the LO condition. No other contrasts for any ROI reached statistical significance (see **Supplemental Table 6** for full table of fNIRS results).

4. Discussion

This study represents a step toward better understanding the influence of common cognitive perturbations on transient aspects of postural control during upright stance. Our hypothesis was partially supported. The transient characteristic ΔEA was able to distinguish between the HI and NO conditions and, to a lesser extent, between the LO and NO conditions. While there was not a significant difference between HI and LO conditions for $\Delta\ln(EA)$, the HI (Cohen’s d = 0.40) condition did exhibit a slightly larger effect size than the LO condition (Cohen’s d = 0.29) relative to the NO condition. Our findings also indicate that transitioning from counting backwards aloud to standing quietly is a plausible explanation for the persistent transient behavior that we observed in the eyes open condition of our previous study (Reed, et al., 2020). Additionally, both the onset and offset of the cognitive tasks were associated with transient increases in postural sway relative to no cognitive task; however, the effects were magnified during the start of the serial subtraction tasks. The larger effects may have been at least partially due to the effects of articulation, as has been previously reported (Dault, Yardley, & Frank, 2003). Overall, there is evidence to support that the common cognitive perturbation of serial subtraction, especially more challenging versions, can contribute to transient periods of increased postural sway during quiet stance. Prior studies have documented the ability for sustained cognitive tasks to elicit increased postural sway; however, this study demonstrates the short timeframe that the perturbing effect can be detected (i.e., within the first 5 seconds of the cognitive task). To our knowledge, this is also the first study to demonstrate that increased postural sway associated with serial subtraction tasks can persist even after counting has ceased.

Initial transient behavior appeared in the HI and LO conditions, much like the transient behavior observed in response to sensory transitions (Boucher, et al., 1995; Brown, et al., 2006; Carroll & Freedman, 1993; Reed, et al., 2020). However, comparing the ΔEA magnitudes for the onset/offset of the counting tasks against our previously collected eyes closed conditions (Reed, et al., 2020) reveals noticeable differences (**Figure 3)**. From these comparisons, the counting tasks elicited a significant transient response, but the magnitude of transient effects was greater when a sensory perturbation of closing one's eyes was present in addition to a counting task. Additionally, these transient effects were more pronounced in older adults than in young adults. Overall, these collective results suggest that sensory perturbations may be more impactful on transient postural behavior than the cognitive perturbations of the present study. However, transient effects may be compounded when sensory and cognitive perturbations are present simultaneously, especially in balance impaired populations.

Although prior studies have used cognitive-motor dual-task paradigms to understand how sensory transitions and cognitive tasks influence postural control (Fraizer & Mitra, 2008; I. Melzer, et al., 2001; Pellecchia, 2003; Shumway-Cook & Woollacott, 2000; St-Amant, et al., 2020), few have approached this with the perspective of looking into transient responses to these transitions. Some studies investigated changes in postural control following a sensory transition while performing a cognitive task (Honeine, et al., 2017), but little research has investigated transient postural control while starting/stopping a cognitive task. The epoch-based analysis used in this study enabled differences in the relative impact of the introduction (i.e., onset) versus cessation (i.e., offset) of the cognitive conditions on postural sway. Analogous to introducing and removing visual information in diabetic patients (Boucher, et al., 1995), larger transient effects were observed for the onset of the cognitive tasks compared to the offset of the tasks. These findings are consistent with postural control being disturbed by the reallocation of attention, either to accommodate the introduction of a concurrent cognitive task or following the withdrawal of a concurrent cognitive task, in an analogous manner to the more well-studied sensory reweighting (Peterka, 2002; Teasdale & Simoneau, 2001). In fact, an interaction between reintegrating sensory information and attentional demand has been reported, raising the question of how dynamic sensory and cognitive demands may compound to challenge postural control (Teasdale & Simoneau, 2001). Because both sensory transitions (e.g., lights turning off in a room) and cognitive perturbations (e.g., being asked a question) are representative of challenging real-life scenarios, investigating the transient behavior at these transition points may provide unique insight into events where postural control is compromised.

It is also notable that an initial increase in EA was not observed in the NO condition (**Figure 3**). This finding provides further support for transient effects not merely being a data collection or processing artifact. Another implication of this finding is the need for researchers to carefully consider how postural control trials are initiated, depending on what aspects of postural control they are attempting to analyze. Even a simple countdown procedure can introduce (potentially unintended) transient effects. The specific mechanisms by which this impact occurs (e.g., increased attentional demand, shift in attention, articulation, etc.) are not discernable from this study and remain opportunities for future work. When designing a postural control study, it may be important to consider whether trials are researcher- or participant-initiated and whether or not to allow participants a period of time to assume quasi-steady state posture prior to recording data. The current study does not enable a direct comparison between researcher- and participant-initiated countdowns to initiate trials, but we can speculate that even listening to a countdown may still be associated with transient aspects of postural control. This speculation is consistent with the elevated point estimates of the first epoch of the Baseline phase, which immediately followed a researcher counting down “3-2-1-Begin”. The duration of the Baseline phase was only 30-seconds, which prevents a direct comparison on the ΔEA metric, but provides some potential support for further exploring the roles of these nuances in experimental approaches on transient postural control characteristics and the mechanisms that drive the observed behavior.

The fNIRS data provide corroborating evidence that the counting tasks were challenging enough to elicit altered PFC activation during the stimulus phase of the protocol. Specifically, an increase in activation (indicated by a decrease in Hbr) in the right BA 46 was observed for both the LO and HI conditions. This area is associated with spatial working memory and executive function involved in decision-making, planning, and problem-solving (Gupta & Tranel, 2012). Furthermore, the decrease in activation in right BA 9 for the HI condition relative to the LO condition corroborates similar findings during serial sevens subtraction (Mirelman, et al., 2014) and trending findings for a non-verbal working memory task (St-Amant, et al., 2020) during standing balance. Collectively, the data support that the concurrent balance and counting tasks elicited an altered neural activation pattern characterized by an increase in BA 46 activation while redistributing blood from right BA 9 to other regions during the HI condition.

Although prior studies have noted the confounding role that articulation can have on postural sway during dual-task balance (Dault, et al., 2003; Yardley, Gardner, Leadbetter, & Lavie, 1999), the measured changes in PFC activation for this study support altered activation to cortical regions associated with executive function and attentional networks (Lundy-Ekman, 2016). The left dorsolateral PFC has been associated with speech, although current evidence suggests the role of this region in speech is for more abstract communication compared to the counting task in this study (Hertrich, Dietrich, Blum, & Ackermann, 2021). However, it is important to note the potential for uncertainty in the ROI actually being measured by the fNIRS system. Although the fNIRS caps were placed carefully with established guidelines, the optode positions were not digitized against subject-specific neuroanatomical locations. Therefore, uncertainty exists in the ROI being analyzed that should be kept in mind when interpreting the fNIRS findings from this study (e.g., BA 46 is close to Broca's area, which would be influenced by speaking). The potential for verbal responses to increase arousal during the cognitive tasks compared to nonverbal cognitive tasks is noteworthy, but secondary to the purpose of this investigation which sought to observe the effects of common cognitive tasks (i.e., serial sevens subtraction) on transient measures of postural control. Given the altered PFC activation that was measured during the LO and HI conditions, there is evidence that the counting tasks effectively challenged participants in this study.

While this study provides new insight into the influence of cognitive perturbations on transient behavior in upright stance, there are certain limitations that should be considered. Isolating the role that articulation had in heightening the perturbing effects of the cognitive task on transient effects will need to be determined in future investigations that include both spoken and silent cognitive perturbations (Dault, et al., 2003). However, our findings provide insight into the impact of common serial subtraction tasks on transient features of postural control. Additionally, participants were wearing a fNIRS cap during all balance trials, which may have influenced postural control compared to typical real-world scenarios. Based on patient-reported outcomes of comfort throughout the trial, and because the cap was worn for all balance trials, we do not believe that this introduced any confounding effects regarding our findings. Furthermore, it is noteworthy that we gave instructions for participants to try to be as still as possible. This approach was aimed to standardize the protocol; however, the inclusion of this instruction may have caused participants to use postural control strategies that deviate from what they would have used in real-world scenarios. Finally, although the ΔEA calculation used here and in previous studies (Reed, et al., 2020) has proven insightful, opportunities persist to optimize the calculation of transient characteristics to improve their sensitivity and reliability (e.g., evaluating other epoch window widths, using an average of steady-state epochs in the ΔEA calculation rather than just the last epoch, etc.). Notably, the findings of the study were essentially identical when calculating Δln(EA) with the steady-state epoch being the epoch immediately preceding the Stimulus phase rather than the last epoch of the Testing phase (see **Supplemental Tables 7 and 8**). This is consistent with the ends of the Baseline and Testing phases largely reflecting ‘steady-state’ balance control, with the transient behavior induced by the counting tasks being the quantified similarly regardless of which basis of steady-state was used. It is also worth noting that the epoch-based approach is likely not appropriate for all types of established CoP outcome measures. For example, prior work has established the minimal number of data points (~2000 data points) for reliable nonlinear analyses such as sample entropy (Yentes, et al., 2013), which would be difficult to achieve with short intervals (~5 seconds) aimed at capturing the initial period of increased sway that follows various perturbations.

5. Conclusion

This study provides a better understanding of the influence of cognitive perturbations to transient behavior in quiet stance postural control. These findings indicate that serial subtraction tasks can contribute to transient periods of increased postural sway during upright standing balance.

Declaration of Interest

This study was supported by a Montana State University Faculty Excellence Grant. The funding source did not have any involvement in the study design, data collection, or data analysis/interpretation. This research did not receive any other specific grant from funding agencies in the public, commercial, or not-for-profit sectors. The authors have no other interests to disclose.

1. References

Al-Yahya, E., Johansen-Berg, H., Kischka, U., Zarei, M., Cockburn, J., & Dawes, H. (2016). Prefrontal Cortex Activation While Walking Under Dual-Task Conditions in Stroke: A Multimodal Imaging Study. *Neurorehabil Neural Repair, 30*, 591-599.

Andersson, G., Hagman, J., Talianzadeh, R., Svedberg, A., & Larsen, H. C. (2002). Effect of cognitive load on postural control. *Brain Research Bulletin, 58*, 135-139.

Asslander, L., & Peterka, R. J. (2014). Sensory reweighting dynamics in human postural control. *J Neurophysiol, 111*, 1852-1864.

Assländer, L., & Peterka, R. J. (2016). Sensory reweighting dynamics following removal and addition of visual and proprioceptive cues. *116*, 272-285.

Barker, J. W., Aarabi, A., & Huppert, T. J. (2013). Autoregressive model based algorithm for correcting motion and serially correlated errors in fNIRS. *Biomedical Optics Express, 4*, 1366.

Boucher, P., Teasdale, N., Courtemanche, R., Bard, C., & Fleury, M. (1995). Postural stability in diabetic polyneuropathy. *Diabetes Care, 18*, 638-645.

Brown, L. A., Cooper, S. A., Doan, J. B., Clark Dickin, D., Whishaw, I. Q., Pellis, S. M., & Suchowersky, O. (2006). Parkinsonian deficits in sensory integration for postural control: Temporal response to changes in visual input. *Parkinsonism & Related Disorders, 12*, 376-381.

Carpenter, M. G., Frank, J. S., Winter, D. A., & Peysar, G. W. (2001). Sampling duration effects on centre of pressure summary measures. *13*, 35-40.

Carroll, J. P., & Freedman, W. (1993). Nonstationary properties of postural sway. *Journal of Biomechanics, 26*, 409-416.

Cinar, E., Saxena, S., McFadyen, B. J., Lamontagne, A., & Gagnon, I. (2021). A prediction model of multiple resource theory for dual task walking. *Theoretical Issues in Ergonomics Science*, 1-24.

Cui, X., Bray, S., & Reiss, A. L. (2010). Speeded Near Infrared Spectroscopy (NIRS) Response Detection. *PLOS ONE, 5*, e15474.

Dault, M. C., Yardley, L., & Frank, J. S. (2003). Does articulation contribute to modifications of postural control during dual-task paradigms? *Cognitive Brain Research, 16*, 434-440.

Doyle, R. J., Hsiao-Wecksler, E. T., Ragan, B. G., & Rosengren, K. S. (2007). Generalizability of center of pressure measures of quiet standing. *Gait and Posture, 25*, 166-171.

Fraizer, E. V., & Mitra, S. (2008). Methodological and interpretive issues in posture-cognition dual-tasking in upright stance. *Gait and Posture, 27*, 271-279.

Goldie, P. A., Bach, T. M., & Evans, O. M. (1989). Force platform measures for evaluating postural control: reliability and validity. *Arch Phys Med Rehabil, 70*, 510-517.

Gupta, R., & Tranel, D. (2012). Memory, Neural Substrates. In *Encyclopedia of Human Behavior* (2nd ed.): Elsevier.

Hauer, K., Pfisterer, M., Weber, C., Wezler, N., Kliegel, M., & Oster, P. (2003). Cognitive Impairment Decreases Postural Control During Dual Tasks in Geriatric Patients with a History of Severe Falls. *Journal of the American Geriatrics Society, 51*, 1638-1644.

Hertrich, I., Dietrich, S., Blum, C., & Ackermann, H. (2021). The Role of the Dorsolateral Prefrontal Cortex for Speech and Language Processing. *Frontiers in Human Neuroscience, 15*.

Honeine, J. L., Crisafulli, O., & Schieppati, M. (2017). Body sway adaptation to addition but not withdrawal of stabilizing visual information is delayed by a concurrent cognitive task. *J Neurophysiol, 117*, 777-785.

Horak, F. B. (2006). Postural orientation and equilibrium: What do we need to know about neural control of balance to prevent falls? *Age and Ageing, 35*, ii7-ii11.

Jacques, S. L. (2013). Optical properties of biological tissues: a review. *Physics in Medicine and Biology, 58*, R37-R61.

Kocsis, L., Herman, P., & Eke, A. (2006). The modified Beer–Lambert law revisited. *Physics in Medicine & Biology, 51*, N91.

Kontos, A. P., Huppert, T. J., Beluk, N. H., Elbin, R. J., Henry, L. C., French, J., Dakan, S. M., & Collins, M. W. (2014). Brain activation during neurocognitive testing using functional near-infrared spectroscopy in patients following concussion compared to healthy controls. *8*, 621-634.

Kozinc, Ž., & Šarabon, N. (2021a). The Effects of Leg Preference on Transient Characteristics of Body Sway During Single-Leg Stance: A Cross-Sectional Study. *Frontiers in Human Neuroscience, 14*.

Kozinc, Ž., & Šarabon, N. (2021b). Transient body sway characteristics during single-leg quiet stance in ballet dancers and young adults. *Journal of Biomechanics, 115*, 110195.

Kozinc, Ž., Trajković, N., & Šarabon, N. (2021). Transient characteristics of body sway during single-leg stance in athletes with a history of ankle sprain. *Gait & Posture, 86*, 205-210.

Kozinc, Ž., Trajković, N., Smajla, D., & Šarabon, N. (2021). The effect of fatigue on single-leg postural sway and its transient characteristics in healthy young adults. *Frontiers in Physiology, 12*.

Kreidler, S., Muller, K., Grunwald, G., Ringham, B., Coker-Dukowitz, Z., Sakhadeo, U., Barón, A., & Glueck, D. (2013). GLIMMPSE: Online Power Computation for Linear Models with and without a Baseline Covariate. *Journal of Statistical Software, 54*.

Lafond, D., Corriveau, H., Hébert, R., & Prince, F. (2004). Intrasession reliability of center of pressure measures of postural steadiness in healthy elderly people. *Archives of Physical Medicine and Rehabilitation, 85*, 896-901.

Lancaster, J. L., Woldorff, M. G., Parsons, L. M., Liotti, M., Freitas, C. S., Rainey, L., Kochunov, P. V., Nickerson, D., Mikiten, S. A., & Fox, P. T. (2000). Automated Talairach atlas labels for functional brain mapping. *Human Brain Mapping, 10*, 120-131.

Lundy-Ekman, L. (2016). Neuroscience: Fundamentals for Rehabilitation. *Elsevier, Fourth Edi*, 525.

Maki, B. E., Holliday, P. J., & Topper, a. K. (1994). A prospective study of postural balance and risk of falling in an ambulatory and independent elderly population. *Journal of Gerontology, 49*, M72-M84.

Massion, J. (1994). Postural control system. *Current Opinion in Neurobiology, 4*, 877-887.

McNevin, N. H., & Wulf, G. (2002). Attentional focus on supra-postural tasks affects postural control. *Human Movement Science, 21*, 187-202.

Melzer, I., Benjuya, N., & Kaplanski, J. (2001). Age-Related Changes of Postural Control: Effect of Cognitive Tasks. *Gerontology, 47*, 189-194.

Melzer, I., Benjuya, N., & Kaplanski, J. (2004). Postural stability in the elderly: A comparison between fallers and non-fallers. *Age and Ageing, 33*, 602-607.

Melzer, I., Kurz, I., & Oddsson, L. I. E. (2010). A retrospective analysis of balance control parameters in elderly fallers and non-fallers. *Clinical Biomechanics, 25*, 984-988.

Menant, J. C., Maidan, I., Alcock, L., Al-Yahya, E., Cerasa, A., Clark, D. J., de Bruin, E. D., Fraser, S., Gramigna, V., Hamacher, D., Herold, F., Holtzer, R., Izzetoglu, M., Lim, S., Pantall, A., Pelicioni, P., Peters, S., Rosso, A. L., St George, R., Stuart, S., Vasta, R., Vitorio, R., & Mirelman, A. (2020). A consensus guide to using functional near-infrared spectroscopy in posture and gait research. *Gait Posture, 82*, 254-265.

Miko, S. C., Simon, J. E., Monfort, S. M., Yom, J. P., Ulloa, S., & Grooms, D. R. (2020). Postural stability during visual-based cognitive and motor dual-tasks after ACLR. *Journal of Science and Medicine in Sport*.

Mirelman, A., Maidan, I., Bernad-Elazari, H., Nieuwhof, F., Reelick, M., Giladi, N., & Hausdorff, J. M. (2014). Increased frontal brain activation during walking while dual tasking: an fNIRS study in healthy young adults. *J Neuroeng Rehabil, 11*, 85.

Mitra, S. (2003). Postural costs of suprapostural task load. *Human Movement Science, 22,* 253-270.

Monfort, S. M., Pan, X., Patrick, R., Singaravelu, J., Loprinzi, C. L., Lustberg, M. B., & Chaudhari, A. M. (2016). Natural history of postural instability in breast cancer patients treated with taxane-based chemotherapy: A pilot study. *Gait and Posture, 48*, 237-242.

Nashner, L., & Berthoz, A. (1978). Visual contribution to rapid motor responses during postural control. *Brain Research, 150,* 403-407.

Pellecchia, G. L. (2003). Postural sway increases with attentional demands of concurrent cognitive task. *Gait & Posture, 18*, 29-34.

Peterka, R. J. (2002). Sensorimotor integration in human postural control. *Journal of Neurophysiology, 88*, 1097-1118.

Piirtola, M., & Era, P. (2006). Force platform measurements as predictors of falls among older people - A review. *Gerontology, 52*, 1-16.

Prieto, T. E., Myklebust, J. B., Hoffmann, R. G., Lovett, E. G., & Myklebust, B. M. (1996). Measures of postural steadiness: Differences between healthy young and elderly adults. *IEEE Transactions on Biomedical Engineering, 43*, 956-966.

Prieto, T. E., Myklebust, J. B., & Myklebust, B. M. (1993). Characterization and modeling of postural steadiness in the elderly: a review. *IEEE Transactions on Rehabilitation Engineering, 1*, 26-34.

Ramdani, S., Tallon, G., Bernard, P. L., & Blain, H. (2013). Recurrence Quantification Analysis of Human Postural Fluctuations in Older Fallers and Non-fallers. *Annals of Biomedical Engineering, 41*, 1713-1725.

Reed, C. A., Chaudhari, A. M. W., Worthen-Chaudhari, L. C., Bigelow, K. E., & Monfort, S. M. (2020). A new perspective on transient characteristics of quiet stance postural control. *PLOS ONE, 15*, e0237246.

Register-Mihalik, J. K., Littleton, A. C., & Guskiewicz, K. M. (2013). Are divided attention tasks useful in the assessment and management of sport-related concussion? *Neuropsychol Rev, 23*, 300-313.

Richer, N., & Lajoie, Y. (2020). Automaticity of Postural Control while Dual-tasking Revealed in Young and Older Adults. *Experimental Aging Research, 46*, 1-21.

Richer, N., Saunders, D., Polskaia, N., & Lajoie, Y. (2017). The effects of attentional focus and cognitive tasks on postural sway may be the result of automaticity. *Gait and Posture, 54,* 45-49.

Riley, M. A., Baker, A. A., Schmit, J. M., & Weaver, E. (2005). Effects of visual and auditory short-term memory tasks on the spatiotemporal dynamics and variability of postural sway. *Journal of Motor Behavior*, *37*, 311-324.

Sample, R. B., Jackson, K., Kinney, A. L., Diestelkamp, W., Reinert, S. S., & Bigelow, K. E. (2016). Manual and Cognitive Dual-tasks Contribute to Fall-Risk Differentiation in Posturography Measures. *Journal of Applied Biomechanics*, 1-24.

Santosa, H., Zhai, X., Fishburn, F., & Huppert, T. (2018). The NIRS Brain AnalyzIR Toolbox. *Algorithms, 11*, 73.

Santosa, H., Zhai, X., Fishburn, F., Sparto, P. J., & Huppert, T. J. (2020). Quantitative comparison of correction techniques for removing systemic physiological signal in functional near-infrared spectroscopy studies. *Neurophotonics, 7,* 035009.

Scholkmann, F., Kleiser, S., Metz, A. J., Zimmermann, R., Mata Pavia, J., Wolf, U., & Wolf, M. (2014). A review on continuous wave functional near-infrared spectroscopy and imaging instrumentation and methodology. *Neuroimage*, *85*, 6-27.

Shumway-Cook, A., & Woollacott, M. H. (2000). Attentional demands and postural control: the effect of sensory context. *The journals of gerontology. Series A, Biological sciences and medical sciences*, *55*, M10-M16.

St-Amant, G., Rahman, T., Polskaia, N., Fraser, S., & Lajoie, Y. (2020). Unveilling the cerebral and sensory contributions to automatic postural control during dual-task standing. *Human Movement Science, 70,* 102587.

Teasdale, N., & Simoneau, M. (2001). Attentional demands for postural control: The effects of aging and sensory reintegration. *Gait and Posture, 14*, 203-210.

Thapa, P. B., Gideon, P., Brockman, K. G., Fought, R. L., & Ray, W. A. (1996). Clinical and Biomechanical Measures of Balance Fall Predictors in Ambulatory Nursing Home Residents. *The Journals of Gerontology Series A: Biological Sciences and Medical Sciences, 51A,* M239-M246.

van der Kooij, H., Campbell, A. D., & Carpenter, M. G. (2011). Sampling duration effects on centre of pressure descriptive measures. *Gait and Posture*, *34*, 19-24.

Wittenberg, E., Thompson, J., Nam, C. S., & Franz, J. R. (2017). Neuroimaging of Human Balance Control: A Systematic Review. *Frontiers in Human Neuroscience*, *11*.

Woollacott, M., & Shumway-Cook, A. (2002). Attention and the control of posture and gait: a review of an emerging area of research. *Gait Posture, 16*, 1-14.

Yardley, L., Gardner, M., Leadbetter, A., & Lavie, N. (1999). Effect of articulatory and mental tasks on postural control. *NeuroReport, 10*, 215-219.

Yentes, J. M., Hunt, N., Schmid, K. K., Kaipust, J. P., McGrath, D., & Stergiou, N. (2013). The appropriate use of approximate entropy and sample entropy with short data sets. *Annals of Biomedical Engineering*, *41*, 349-365.

Yogev-Seligmann, G., Hausdorff, J. M., & Giladi, N. (2008). The role of executive function and attention in gait. *Movement Disorders*, *23*, 329-342.

Zhai, X., Santosa, H., & Huppert, T. J. (2020). Using anatomically defined regions-of-interest to adjust for head-size and probe alignment in functional near-infrared spectroscopy. *Neurophotonics*, *7*, 035008.

Figure Captions

Figure 1. Diagram of researcher cues and participant responses in each cognitive perturbation condition. Visual schematic of NO, LO, and HI conditions with researcher verbal cues represented by the shaded callout shapes and participant verbal responses represented by the outlined boxes. All conditions were initiated by the researcher countdown ‘3-2-1-Begin’, with trials starting upon ‘Begin’. The separate phases of the 100-second trial are also depicted with 0-30 seconds representing the Baseline phase, 30-40 seconds representing the Stimulus phase, and 40-100 seconds representing the Testing phase.

Figure 2. Transient behavior for EA across all three cognitive perturbation conditions. Blue circles, pink squares, and green diamonds represent the time-series data for the HI, LO, and NO cognitive perturbation conditions, respectively. Values correspond to mean ± standard error of the mean for each epoch. Values for the HI and NO conditions are slightly jittered on the Time axis to avoid data points overlapping and for ease of interpretation. The red shaded area represents the Baseline phase, the blue shaded area represents the Stimulus phase, and the non-shaded area represents the Testing phase. The regions used for onset and offset of cognitive conditions are boxed.

Figure 3. Mean ΔEA values across various sensory and cognitive perturbations. Adding a sensory perturbation in addition to a cognitive task was associated with increase in the transient effects, which is quantified with ΔEA. Onset of sensory and/or cognitive perturbations were associated with larger transient effects compared to offset of perturbations. Older adults (OA) showed exacerbated transient effects under sensory plus cognitive perturbations relative to

younger adults (YA). Data markers correspond to mean values and bars correspond to standard errors. †Several data points are from previously reported work (i.e., (Reed, et al., 2020)) to provide broader context for factors that influence the transient characteristics.

Figure 1

Click here to access/download;Figure;HMS_Figure1.eps

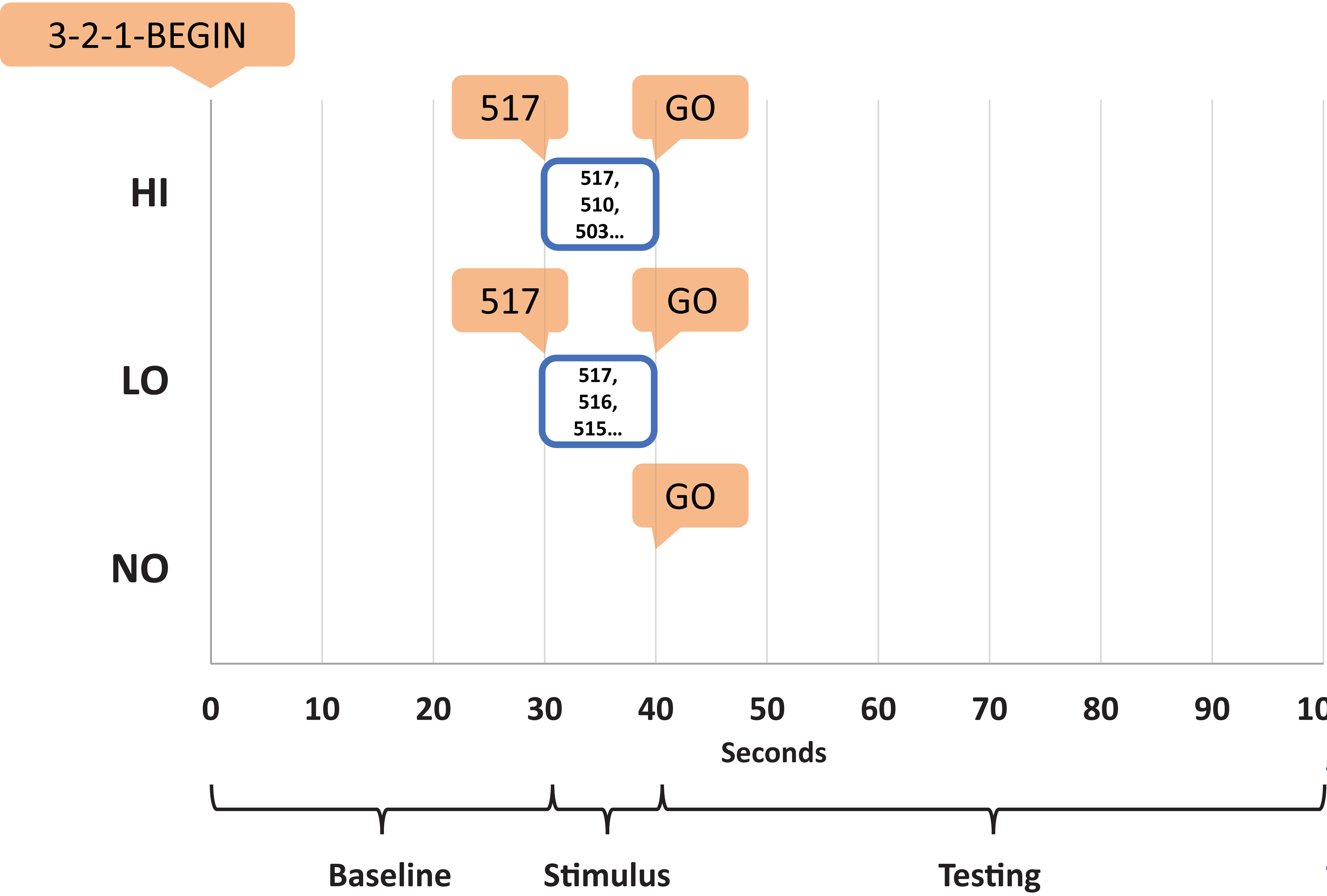

Figure 2

Click here to access/download;Figure;HMS_Figure2_v2.eps

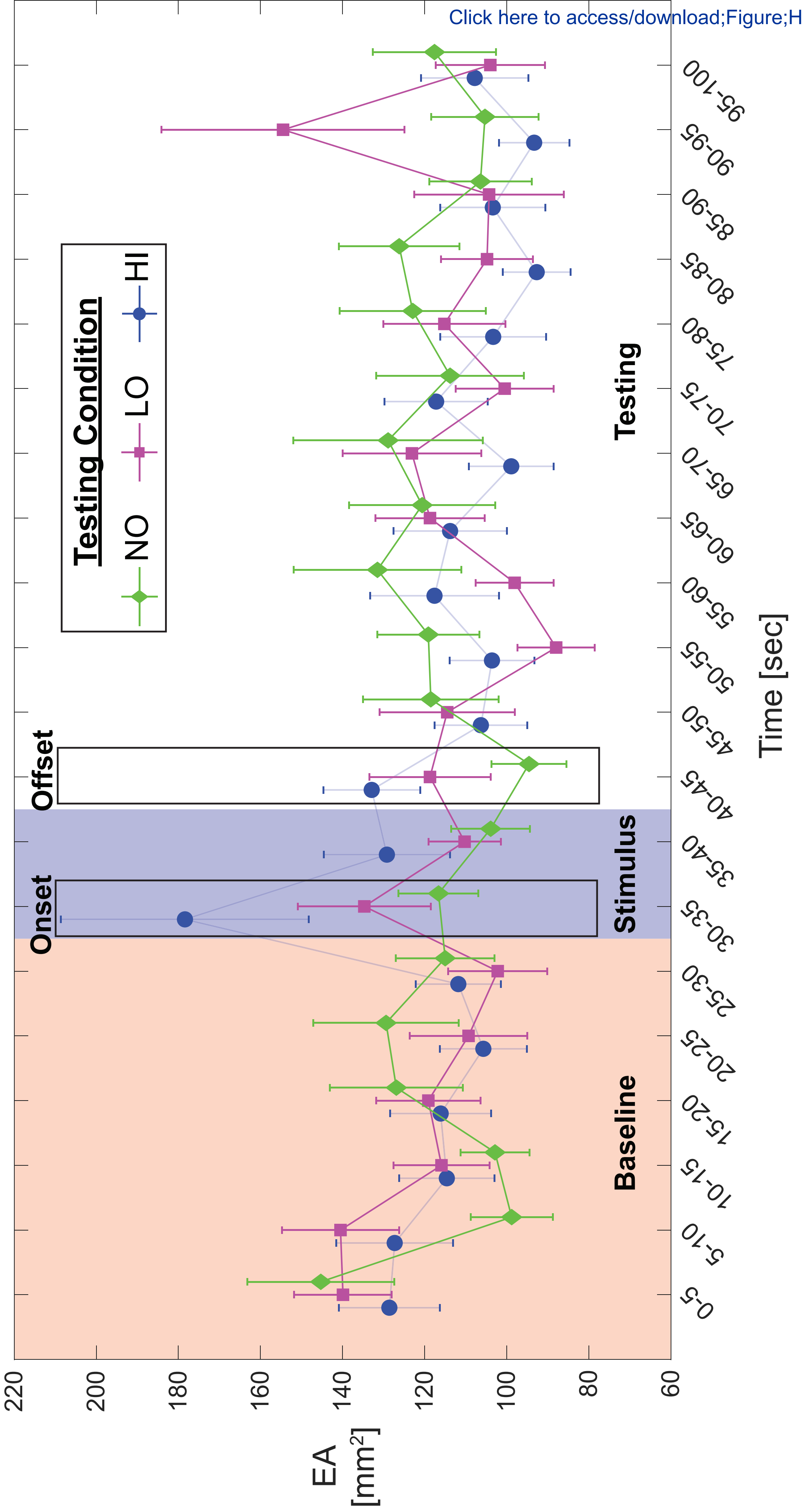

Figure 3

Click here to access/download;Figure;HMS_Figure3_v3.eps

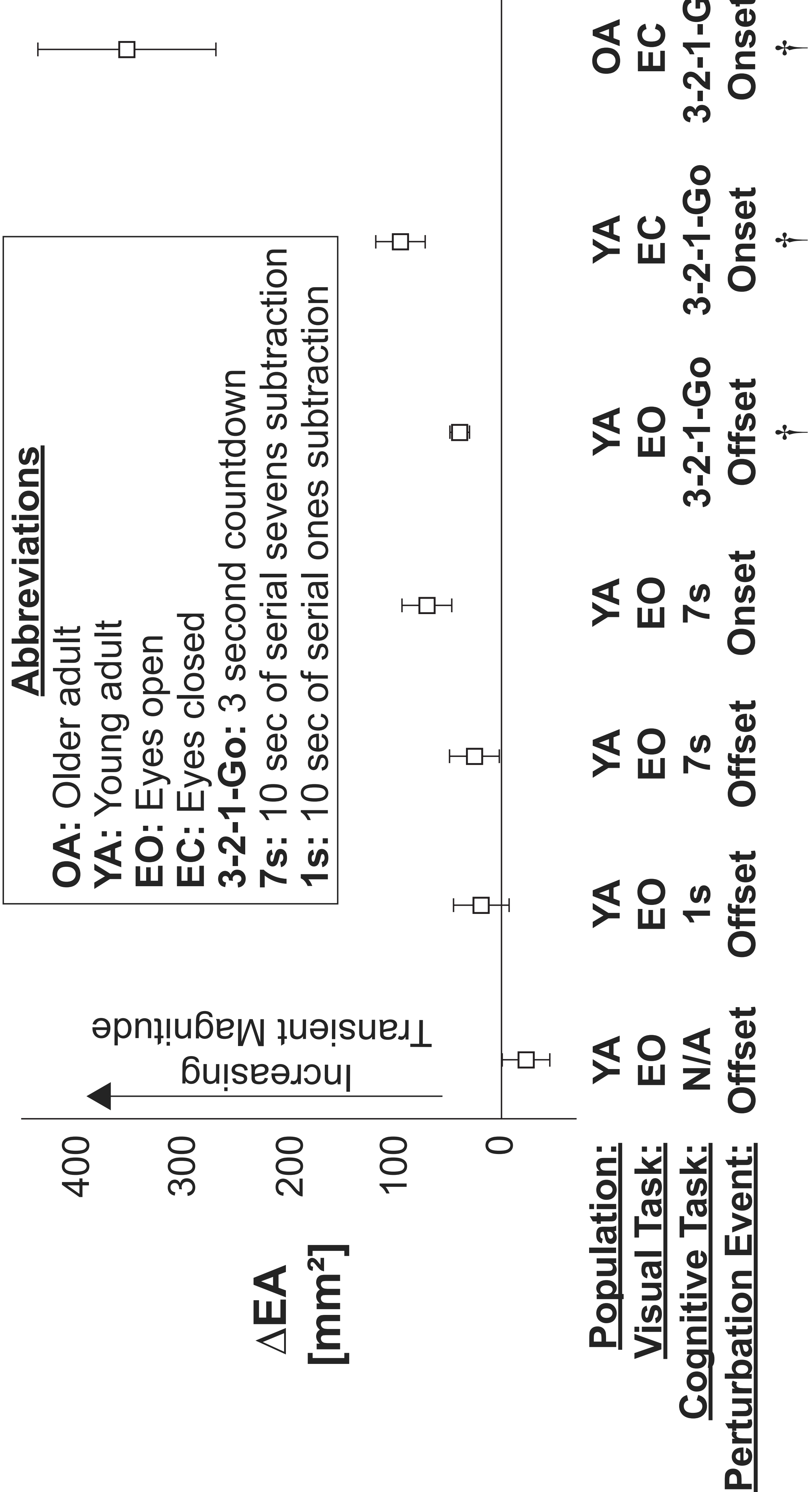

Table 1. Performance on Cognitive Tests during 10-Second Stimulus Phase. Values are presented as Mean (Standard Error).

Performance Metric	**LO**	**HI**	***P*-value**
Numbers Spoken	5.6 (1.3)	3.0 (1.1)	<0.001*
Accuracy	99% (2%)	92% (11%)	0.039[†]

* indicates comparison was made with a paired T-test.

[†] indicates comparison was made with a Sign test

Table 2. Descriptive Statistics and Model Results for Natural Logarithmic ΔEA for Balance Conditions for Onset and Offset of Cognitive Stimuli. Values are presented as Mean (Standard Error) or F-statistic (*P*-value) for Condition or Stimulus Event fixed factors. * indicates statistical significance ($P<0.05$).

Outcome Measure	**Stimulus Event**	**NO**	**LO**	**HI**	**Condition *P*-value**	**Event *P*-value**
Δln(EA)	**Onset**	0.14 (0.09)	0.33 (0.12)	0.43 (0.08)	$F_{2,97}$ = 8.46 (<0.001*)	$F_{1,97}$ = 5.68 (0.019*)
	Offset	-0.17 (0.12)	0.20 (0.11)	0.30 (0.10)		

* $P < 0.05$

Table 3. Tukey Post-Hoc Comparisons between Cognitive Perturbation Conditions for Natural Logarithmic Analysis (i.e., Δln(EA)).

Natural Logarithm	
Comparison	**Cohen's d (Adjusted *P*-value)**
LO-NO	**0.29 (0.013)***
HI-NO	**0.40 (<0.001)***
HI-LO	0.11 (0.534)

* $P < 0.05$
Values are: Cohen's d (Adjusted *P*-value)

Author Statement

Cody A. Reed: Conceptualization; Methodology; Formal analysis; investigation; data curation; Writing – original draft; Writing – Review & editing; Visualization; Project administration. **Camryn DuBois**: Formal analysis; investigation; data curation; Writing – Review & editing. **Keith A. Hutchison:** Writing – Review & editing. **Theodore J. Huppert:** Methodology, Writing – Review & editing, Supervision. **Scott M. Monfort** – Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – Review & editing, Visualization, Supervision, Funding acquisition

Supplementary Tables

fNIRS Layout