Novel automaticity index characterizing dual task walking reveals a cognitive ability-related decline in gait automaticity.

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Abstract

Gait automaticity refers to the ability to walk with minimal recruitment of attentional networks typically mediated through the prefrontal cortex (PFC). Reduced gait automaticity is common with aging, contributing to an increased risk of falls and reduced quality of life. A common assessment of gait automaticity is to examine PFC activation via near-infrared spectroscopy (fNIRS) during dual-task (DT), such as walking while performing a cognitive task. However, interpretation of PFC activity without considering task performance could be misleading. For example, greater PFC activation could be interpreted as worse gait automaticity when accompanied by worse DT performance but as compensatory when accompanied by better DT performance. Thus, there is a need to incorporate performance in interpretation of PFC measurements. To address this need, we propose a novel automaticity index as an analytical approach that combines changes in PFC activity with changes in DT performance to quantify gait automaticity. The efficacy of the index was verified in 173 participants (≥65 y/o) who completed DTs with two levels of difficulty while PFC activation was recorded with fNIRS. The two DTs consisted of reciting every other letter of the alphabet while walking over either an even or uneven surface. We found that compared to PFC activation, our novel index better reflected the decrease in automaticity as DT difficulty increases. Furthermore, decreased cognitive ability was related to worse automaticity index, but not PFC activation or DT performance, suggesting that the index is more sensitive to individual characteristics that influence automaticity. In sum, the proposed automaticity index better quantified the between task and individual differences in automaticity by providing a unified measure of gait automaticity that includes both brain activation and performance. This new approach opens exciting possibilities to assess subject-specific deficits and compare rehabilitation outcomes from gait automaticity interventions.

(304 words)

Introduction

Community mobility, the ability to move around in the community, is essential for independent living (Patla & Shumway-Cook, 1999; Rantakokko et al., 2016; Rosso et al., 2013; Sheppard et al., 2013). Successful community mobility requires gait automaticity (Brustio et al., 2018; Clark et al., 2014; Van Swearingen & Studenski, 2014), which refers to the automatic control of walking with minimal recruitment of attentional networks primarily residing in the prefrontal cortex (PFC) (Clark, 2015; Van Swearingen & Studenski, 2014). Automatic control of walking allows attentional resources to be reserved to process environmental conditions (e.g., monitoring oncoming traffic or varying ground terrain), which supports safe community mobility. As a result, reduced gait automaticity may contribute to an increased risk of falls (Gschwind et al., 2010; Montero-Odasso et al., 2011). Gait automaticity declines with age (Clark, 2015; Gschwind et al., 2010; Montero-Odasso et al., 2011; Van Swearingen & Studenski, 2014) but we do not currently have a standardized way to quantify gait automaticity.

Gait automaticity is traditionally evaluated by challenging participants to complete a dual-task assessment (DT, i.e., walking and performing a cognitive task simultaneously) and comparing the performances in DT relative to single-task assessments (ST, i.e., either walking or performing a cognitive task) (Paul et al., 2005). High automaticity is reflected by a similar performance in DT and ST, under the assumption that individuals with good automaticity would perform similarly in the cognitive task with or without walking, because walking is automated and requires minimum attentional resources (Clark, 2015). However, behavioral measures alone from DT does not provide details on the neural resources that are required to complete the task. With the recent development of noninvasive brain imaging technologies such as functional near-infrared spectroscopy (fNIRS), use of attentional resources can be evaluated more directly by measuring the cortical activation of the PFC (Clark, 2015; Herold et al., 2017; Holtzer et al., 2011; Menant et al., 2020). DT paradigms integrated with fNIRS-based PFC measurements provide a promising means to assess gait automaticity.

It is challenging to interpret PFC measurements and task performance independently during automaticity assessments. Specifically, low PFC activation concurrent with good task performance may be indicative of high automaticity. In contrast, when low PFC activation is accompanied by poor task performance, it could indicate the task is too difficult for the participant such that their cognitive resources are insufficient to cope with the task demand, resulting in disengagement and low PFC activation (Reuter-Lorenz & Cappell, 2008). In this case, the low PFC activation corresponds to participants with low automaticity where the cognitive reserve and the range of task difficulties they could handle are limited. On the other hand, a high PFC activation paired with poor task performance typically corresponds to poor automaticity (Fettrow et al., 2021), but a high PFC activation with maintained task performance could also be interpreted as successful compensation from PFC for other regions whose structures and integrities have declined with aging (Fettrow et al., 2021; Maillet & Rajah, 2013; Park & Reuter-Lorenz, 2009). Similarly, the same task performance can be achieved with low PFC activation (sign of automaticity) or high PFC activation (sign of effort and compensation) . Therefore, simply equating PFC activations or task performance with automaticity without considering them together is not sufficient to quantify gait automaticity.

To address this need, we propose a novel automaticity index that combines changes in PFC activity with changes in DT performance to quantify gait automaticity. The objective of the study was to test the efficacy of the index to differentiate 1) between tasks within the same subjects, and 2) between subjects. For objective 1, to compare between tasks, we computed the automaticity index in older participants (≥65 years of age, n=173) who completed two difficulty levels of DT. We expected the automaticity index would be smaller at greater levels of task difficulty. For objective 2, to compare between subjects, we tested if individual's cognitive ability, measured by Mini-Mental State Exam scores, are related to automaticity. We anticipated that better cognitive ability is correlated with better automaticity.

Materials and Methods

Participants

The data included participants from three previously published studies: Program to Improve Mobility in Aging (PRIMA), n = 42(Brach et al., 2020); Neural Mechanisms of Community

Mobility (NMCM), n = 29 (Aizenstein et al., 2008); and Move Monongahela-Youghiogheny Healthy Aging Team (Move MYHAT), n =102 (Ganguli et al., 2010). The 3 datasets included similar experimental protocols but were collected for different purposes across two different lab spaces with two different fNIRS systems and with different experimenters.

All study participants were at least 65 years old, able to walk unassisted and had no major neurological conditions. More details of the medical conditions and inclusion criteria were reported in the published studies. The Institutional Review Board at the University of Pittsburgh approved the studies and all participants gave written informed consent.

Participant Characteristics

In all studies, age, sex, and highest level of education were self-reported. General cognitive ability was assessed using the Mini-Mental State Exam (MMSE), a commonly used screening instrument for cognitive impairments (Folstein et al., 1975). For the PRIMA participants, the Modified Mini-Mental State (3MS) Test was performed and the MMSE scores were derived from the 3MS scores by extracting only items equivalent to the MMSE and recalculating a score.

Experimental Paradigm

Participants performed single or dual tasks on an oval track with a 15-meter straight walkway that has a standard surface on one side (even) and wood prisms underneath carpets on the other side (uneven(Hoppes et al., 2020; Thies et al., 2005). All Participants performed four experimental trials and each trial included a pseudo-randomized presentation of four conditions used here: two single tasks (ST) and two dual tasks (DT) (Figure 1). Single tasks include a motor single-task, walking on the even surface (walk), and a cognitive single-task, standing while reciting every other letter of the alphabet starting from A (standABC; Brandler et al., 2012; Holtzer et al., 2011; Verghese et al., 2012). The single tasks were used as a reference to compute the change in performance during DT to account for the different baseline abilities of each participant. The DT conditions require performing the cognitive tasks while walking on the even (evenABC) or uneven surfaces (unevenABC). The unevenABC condition was considered a harder DT condition than the evenABC because of the increased challenge on balancing and walking on the uneven floor surface.

The task duration was 20s for standABC. The duration for the walk (motor ST) and DTs varied depending on the time participant took to walk the 15m straightway. Every condition was preceded by a quiet standing for 20s, which is the baseline for fNIRS recordings. The quiet standing allowed the hemodynamic response to return to rest level such that relative changes in oxygenation of the blood can be computed for each task condition compared to quiet standing.

Data Collection

PFC activation was measured using fNIRS which measures changes in blood oxygenation based on the distinct light absorption properties of oxygenated (Hbo) and deoxygenated (Hbr) hemoglobin (Hoppes et al., 2020; Miyai et al., 2001; Perrey, 2014). Participants wore an eight-channel continuous wave fNIRS headband (Octamon, Artinis Medical Systems, Netherlands) over their forehand during the entire experiment. The headband contained two detectors and eight sources covering both the left and right PFC regions. Near infrared transmitted at 840nm and 760 nm was used to detect changes in Hbo and Hbr. Data was sampled at 10Hz and collected with the software OxySoft (Artinis Medical Systems, Netherlands).

Motor performance was quantified by gait speed (m/s). Gait speed is computed by distance (15m) divided by the time to walk the 15-meter walkway where time was measured by a stopwatch. Cognitive performance was measured by the rate of correct letters of alphabet generated per trial duration (correct letters/s). Average motor and cognitive performance for each condition across the four trials is reported.

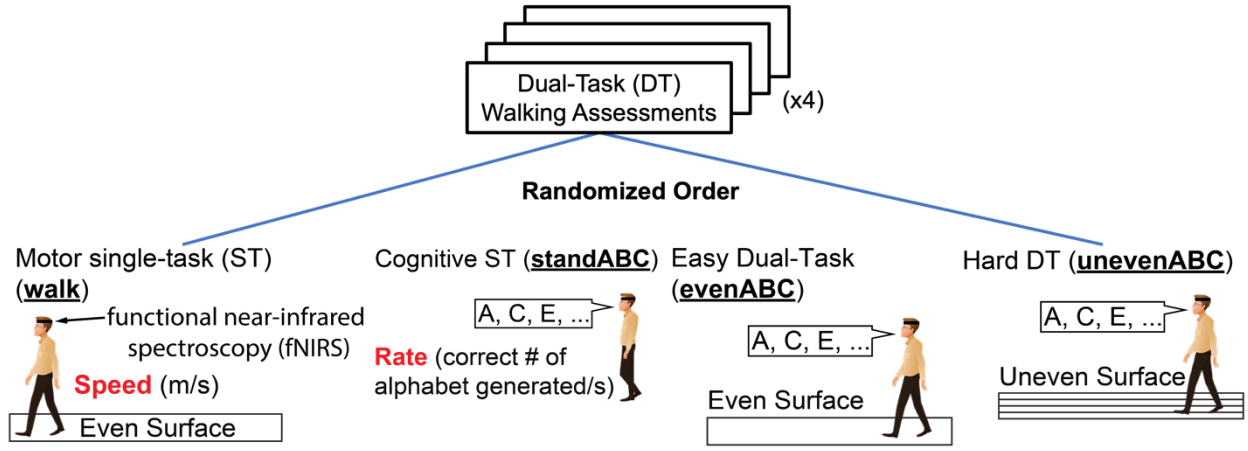

Figure 1. Experiment Protocol. Participants performed 4 trials of dual-task (DT) assessments. Each trial includes a motor single-task (ST): walking on the even surface, a cognitive ST: standing and reciting every other letter of the alphabet (standABC), and 2 DT: reciting every other letter of the alphabet while walking on an even (evenABC) or uneven (unevenABC) surface. The tasks within a trial are presented in pseudo-random order. Motor performance is measured by gait speed (m/s) and cognitive performance is measured by the rate of correct letters generated. Prefrontal cortex activations were measured by functional near-infrared spectroscopy throughout the trial.

fNIRS Data Analysis

fNIRS data was analyzed using the NIRS Brain AnalyzIR toolbox (Santosa et al., 2018) in MATLAB (Mathworks, Natick, Massachusetts). Light intensity was first converted to Hbo and Hbr measurements using the modified Beer-Lambert law with partial path length factor of 0.1. A canonical model with the condition timing and duration was applied. The model was solved with an iteratively autoregressive pre-whitening least square approach to minimize motion artifacts. A student's t-test was then performed on the regression coefficients and the t-score represents the changes in Hbo or Hbr in each task compared to quiet standing. The results across 4 trials for the 8 channels covering the whole PFC are combined using the toolbox to generate 1 ΔHbo and 1 ΔHbr per task for each participant. Typically, an increase in PFC activity will be represented by an increase in oxygenated hemoglobin (i.e., a positive Δhbo value) and a decrease in deoxygenated hemoglobin (i.e., a negative ΔHbr value).

Δhbo had a stronger signal to noise ratio and therefore was used as the main measure of PFC activation for the remainder of the article. However, the same approach is applicable to both Δhbo and ΔHbr measurements (supplemental materials).

Automaticity index

The goal of the automaticity index is to create a single monotonic axis that combines performance and PFC activation to estimate automaticity where a larger index will always represent worse

automaticity (Fig. 2). Worse automaticity is reflected by more attentional interference between dual tasks where the two tasks competing for the same resources , leading to decreased task performance and increased recruitment of attentional resources (i.e., higher PFC activation).

The automaticity index combining cortical activation and performance is defined as the following:

$$\text{AutomaticityIndex} = \text{Gain} * PFC_{Activation} \qquad \text{(Eq. 1)}$$

$$\text{where Gain} = f(\Delta Performance) = e^{-\alpha * \Delta Performance}$$

$$\Delta Performance = \frac{\Delta Motor}{Motor_{ST}} + \frac{\Delta \text{Cognitive}}{Cognitive_{ST}} = \frac{Speed_{DT} - Speed_{ST}}{Speed_{ST}} + \frac{Rate_{DT} - Rate_{ST}}{Rate_{ST}}$$

ST = single-task conditions

DT = dual-task conditions (evenABC or unevenABC)

Speed = gait speed (m/s)

Rate = rate of correct letters of alphabet generated (letters /s)

Figure 2 demonstrates the process to compute the automaticity index using the one of the dataset with three example subjects highlighted to visualize the transformation of the data. The automaticity index is generated by scaling $PFC_{Activation}$ with a gain that is a function of performance changes during DT.

Performance change is measured by $\Delta Performance$ (Fig. 2A), defined as the combined changes in cognitive and motor performances from ST to DT, normalized to performance in domain-specific ST (standABC and walking, respectively). The normalization is done to account for individual differences in walk speed and alphabet performance at baseline. $\Delta Performance$ included both motor and cognitive performances and weighted them equally because participants received no specific instruction about prioritization and the combined $\Delta Performance$ should account for different strategies participants employed during dual task (Laguë-Beauvais et al., 2015; Verghese et al., 2007; Yogev-Seligmann et al., 2010). The definition of $\Delta Performance$ is similar to dual-task cost in existing literatures (Brauner et al., 2021; Longhurst et al., 2022). A more negative $\Delta Performance$ value represents a larger cost to DT. In other words, a negative $\Delta Performance$ means the participants walked slower and/or generated fewer correct alphabet letters during DT compared to ST. A positive $\Delta Performance$ represents increased performance in DT from ST.

A negative sign was added before $\Delta Performance$ because we expected performance to decrease during DT (i.e., $\Delta Performance \leq 0$; Fig. 2A, majority of data points < 0). The negative $\Delta Performance$ reflects cognitive-motor interference during DT, which is expected in populations where gait automaticity is reduced, such as older adults.

The exponential weighting in the gain is chosen such that 1) performance decreases ($\Delta Performance < 0$) scale the index up, with a large decrease weighted much more than a small decrease (Fig. 2B), 2) performance improvements ($\Delta Performance > 0$, less common occurrences; Fig. 2B) scale the index down, but to a much smaller extent, and 3) unchanged performance will result in an index that is equal to the PFC activations. This weighting focuses on the quantification of automaticity in participants with decreased performance, which is expected in populations of interest for most studyies of gait automaticity.

A hyperparameter α is included in the gain definition to regulate the impact of $\Delta Performance$ on the automaticity index. By design of the experimental protocol, a harder DT condition (unevenABC) should introduce more attentional interferences between the tasks and resulting in less automaticity. Consistent with the task design, the majority of participants decreased performance as task difficulty increased (76% in NMCM, 76% in PRIMA, and 68% in MMH; Fig. 3). As α increases, $\Delta Performance$ was weighted more in the index. As a result, the majority of the participants who behaved consistently with the task design will now have an automaticity index that increases with task difficulty as expected. However, too large of an α will lead to exponential growth of the automaticity index and potentially create additional outliers in the scaled dataset. Therefore, α was chosen by maximizing the number of subjects that increase the index value as the task became harder while minimizing the number of outliers created by the scaling. Specifically, the objective function is defined as:

$$\text{Objective function} = \%(\text{AutomaticityIndex}_{\text{unevenabc}} > \text{AutomaticityIndex}_{\text{evenabc}}) - \%\text{outliers}$$

Outliers are defined as values that are more than three scaled median absolute deviation from the median, which is a robust measure of dispersion and outliers (Leys et al., 2013). The objective function value was evaluated for $\alpha \in [0, 5]$ with 0.1 increments. The optimal α was chosen as the smallest α that maximizes the objective function. The search range starts at $\alpha = 0$ where the gain from $\Delta Performance$ is 0 and automaticity index is equal to the PFC activation, which is the current standard in the field. The upper bound 5 was chosen from observing the trajectory of the objective function in the dataset.

To maintain the monotonic property of the automaticity index and the relative differences across people and conditions, we turned all $\text{PFC}_{\text{Activation}}$ values positive by shifted all PFC activity data, i.e., Δhbo measurements, by an offset (Fig. 2C, D), specifically:

$$PFC_{activation} = f(Raw\ PFC\ Activities)$$

$$= f(\Delta\text{hbo})$$

$$= \Delta\text{hbo} + \min(\Delta\text{hbo}) + \varepsilon$$

$$\varepsilon > 0$$

When neural activity increases, Hbo increases locally, resulting in a positive Δhbo during the task compared to rest. If we were to use Hbr to represent the PFC activations, Hbr is first sign flipped

to maintain the convention where higher $PFC_{activation}$ always represents more PFC activities, specifically:

$$\textit{If using Hbr,} \qquad PFC_{activation} = f(-\Delta\mathrm{Hbr})$$

$$= -\Delta\mathrm{Hbr} + \min(-\Delta\mathrm{Hbr}) + \varepsilon$$

$$\varepsilon > 0$$

ε is added to keep all PFC activation values positive (>0). Notice that Eq. 3 is a linear operation. Thus, the specific value of ε doesn't impact the results. In this case we chose $\varepsilon = 1$ for simplicity (Fig. 2D). With this shift, we cannot tell if a subject increased or decreased PFC activities during a task compared to resting by examining the sign of the PFC activations, but this linear operation does not change the relative relationship between tasks (Fig. 2C, D; the slope of the lines remain the same) and subjects (Fig. 2C, D; for example, yellow participant is always higher than the red and blue participants before and after shifting). In other words, the linear operation does not impact the goal of the automaticity index, which is to compare gait automaticity across tasks and individuals. A higher value before or after the shifting will always represent more PFC activation during the task.

The full process to compute the automaticity index is demonstrated in Figure 2. The blue sample is a typical example that behaves as we expected from the task design. As task difficulty increases, the blue sample participant decreased performance (Fig. 2A, negative slope) and increased PFC activation (Fig. 2C, D, positive slope), suggesting the harder task had more interference between walking and the alphabet tasks and required more attentional resources. In other words, the harder task was performed with less automaticity. As a result, the harder task had a larger automaticity index (Fig. 2E, positive slope). In contrast, the yellow sample subject increased performance (Fig. 2A) and decreased PFC activation (Fig. 2C, D) as the task became harder, suggesting the harder task was performed with improved automaticity (Fig. 2E, lower value in automaticity index for the harder task). This could result from the task design not being challenging enough for the participant or the participant was not fully engaged in the easy task.

The Index is also effective at differentiating between participants. The red and blue samples had similar patterns of performance (Fig. 2A, negative slopes for both red and blue) and PFC activations (Fig. 2C, D, positive slopes), but the red participant had better performance than blue (ΔPerformance red > blue), which means that with similar PFC resources, the red participant was able to use the resources more effectively for the task challenge whereas the blue sample could not. As a result, the red sample should be considered to have better automaticity and lower automaticity index values (Fig. 2E, red much smaller than blue).

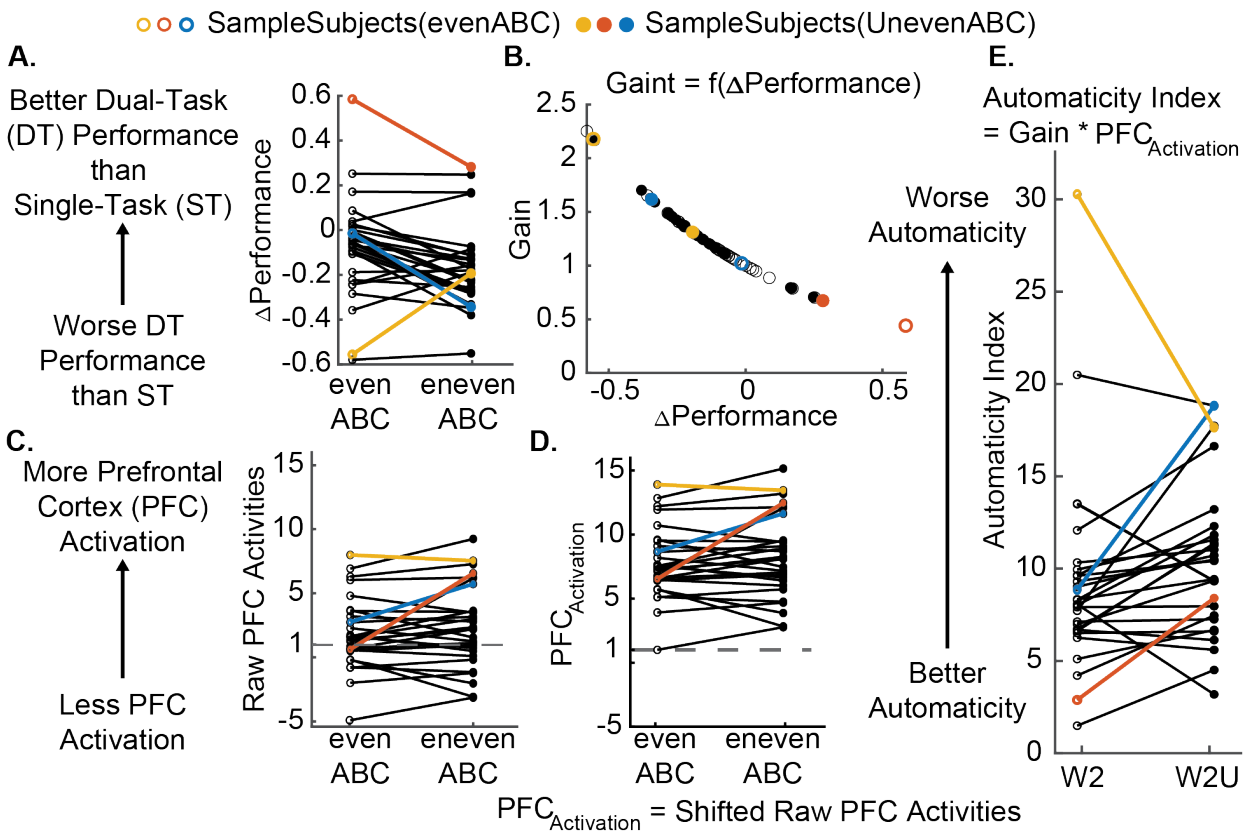

Figure 2. Schematics illustrating the process to compute the automaticity index. The displayed example is one of the included dataset with 3 example subjects highlighted (yellow, red, and blue). The evenABC (easier dual task, DT) task is represented by hollow circles and the unevenABC task is marked with filled circles. **A.** Normalized performance change from single-task (ST) baseline. The performance combines both motor and cognitive performances. A positive value indicates performance is better in DT than ST. **B.** Calculation of the gain from *Δ*Performance. A large decrease in performance is mapped to a large gain (yellow empty circle). **C.** The raw measure of PFC activities, which are t-scores representing changes in oxygenated hemoglobin (Hbo) concentration from rest to DT. Positive value indicates increased Hbo concentration in DT compared to rest standing. Negative value indicates a decrease in Hbo concentrations in DT. **D.** The second term in the automaticity index equation, $PFC_{Activation}$, which simply shifts raw prefrontal cortex (PFC) activity values to be above or equal to 1. **E.** The computed automaticity index, which is the multiplication of the gain and the PFC Activation.

Statistical Analysis

Unadjusted linear regressions were performed to test if automaticity index, PFC activation, and performance are related to MMSE scores. Models were then adjusted for age, sex, and highest level of education to test if the relation between automaticity index and MMSE was robust after controlling for demographics. Model significance was determined by F-test comparing the regression model with a constant model. We reported the ordinary R^2 for the model and standardized coefficient estimates with their respective standard deviations and p-values. All analyses were performed in MATLAB and a statistical significance of $\alpha = 0.05$ was used.

Two samples were identified as outliers and removed from the analysis, resulting in a regression model with n = 171. One did not follow the instruction to recite every other letter of the alphabet and one was the only sample having less than high school degree.

Results

Demographics, cognitive test results, performances and fNIRS measurements of PFC activations in dual tasks for each study are shown in Table 1.

Table 1. Demographic, clinical assessments results, task performances and PFC activations (Hbo) of the study samples. All data shown as mean±SD except for Sex, which is binary, Race and Highest level of education, which are categorical.

Variables	**Mean(SD) or n(%)**
Sample size	173
Age (years)	73.9 ± 5.6
Female, n (%)	108 (62.4%)
Highest level of education, n (%)	
Less than high school or others	1 (0.6%)
High school/equivalent	42 (24.3%)
College	87 (50.3%)
Postgraduate	43 (24.9%)
Cognitive Assessments Results	
Mini-Mental State Exam (MMSE) score (max 30)	28.4 ± 1.8
Gait speed at walk (motor single-task, m/s)	0.97 ±0.14
Gait speed at evenABC (m/s)	0.83 ±0.17
Gait speed at unevenABC (m/s)	0.78 ±0.16
Rate of correct alphabet letters at standABC (cognitive single-task, number/s)	0.58 ±0.14
Rate of correct alphabet letters at evenABC (number/s)	0.62 ±0.15
Rate of correct alphabet letters at unevenABC (number/s)	0.59 ±0.13
Change in oxygenated hemoglobin (ΔHbo) at evenABC (t-stats)	1.88 ± 2.75
ΔHbo unevenABC (t-stats)	2.43 ± 3.22

Automaticity index increases as task difficulty increases.

We expect a harder task will be performed with less automaticity, i.e., increased automaticity index (Fig. 3A, 3B top left panel); specifically, the harder task will require more attentional resources, i.e., increased PFC activation (Fig. 3A bottom left panel), and result in poorer performance (Fig. 3B bottom left panel)

Only 57% of subjects increased PFC activation as the task became harder (Fig. 3A bottom middle panel), showing no clear evidence of increase in attentional control as task difficulty increased. However, 73% of participants increased automaticity index (i.e., had worse automaticity) as task difficulty increased (Fig. 3A top middle panel), matching our intuition that more challenging tasks would be performed with lower automaticity. Notice that the change in the percentage mostly consist of the grey participants who moved from an unexpected decrease in PFC activation as task difficulty increases (Fig. 3A bottom right) to an increase in automaticity index in the expected

direction (Fig. 3A top left). These grey participants recruited less PFC as the task gets harder but their performance declined, suggesting that PFC resources are not being used effectively as needed by the task demand, which is a sign of reduced automaticity.

In comparison, a larger percentage of participants (71%) decreased performance as task became harder (Fig. 3B bottom right panel). The grey participants in the right panel had an unexpected increase in performance with harder task difficulty but had an increase in automaticity index. These may be indivdiuals who improved performance at a cost of greater PFC recruitment. The increased PFC recruitment could represent a compensatory strategy to cope with the task demand, which would correspond to reduced automaticity.

The automaticity index better distinguishes between task difficulty within the participants by demonstrating the expected decrease in automaticity as task difficulty increases compared to PFC activation alone.

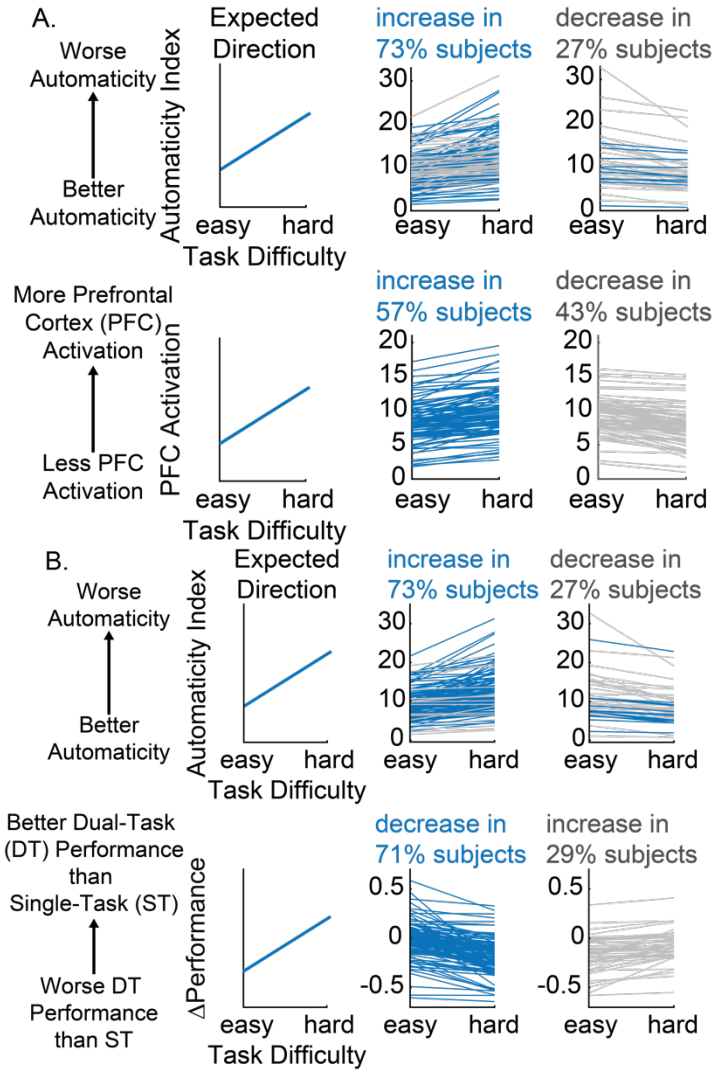

Figure 3. Comparison between automaticity index, PFC activations, and *Δ*Performance as task difficulty increases. A. Comparison between automaticity index and PFC activation. Blue always represents participants who showed expected increase in PFC activation (bottom middle panel) and grey

always represents participants who decreased PFC activation (bottom right). Color scheme in the top panel represents how participants from different groups at the bottom panel moved into different categories (increase or decrease) in automaticity index. Notice that some participants with unexpected decrease in PFC activation will now have expected increase in automaticity index after considering performance (grey in top middle and bottom right). **B.** Comparison between automaticity index and ΔPerformance. Blue always represents participants who showed expected decrease in ΔPerformance as task becomes harder (bottom middle panel) and grey always represents the ones who increased ΔPerformance (bottom right). Color scheme in the top panel represents how participants from different groups at the bottom panel moved into different categories (increase or decrease) in automaticity index.

Greater automaticity index is related to worse cognitive function.

Higher MMSE was associated with lower automaticity index across both tasks (Table2; evenABC: F=9.97, p = 0.002, R^2=0.06; unevenABC: F=9.11, p = 0.003, R^2=0.05) and this association was robust to adjustment by age, sex, and highest level of education (Table 3; Figure 4; evenABC: F=3.09, p = 0.01, R^2=0.09; unevenABC: F=2.33, p = 0.04, R^2=0.07). Higher MMSE was also associated with lower PFC activation at the evenABC task (F=5.57, p = 0.02, R^2=0.03), but this relation was weaker after adjusting for the covariates (F=2.11, p = 0.07, R^2=0.03).

To compare the impact of MMSE across the models, the standardized β is reported. Briefly, the standardized β represents in standard deviation unit how much a unit increase in MMSE will impact the dependent variable. The association between MMSE and automaticity index had the largest standardized β across both two tasks (Table2; evenABC: $\beta = -0.23 \pm 0.07,\ t = -3.16,\ p = 0.002$; unevenABC: $\beta = -0.22 \pm 0.07,\ t = -3.02,\ p = 0.003$).

In sum, MMSE scores was more strongly correlated with automaticity index than PFC activations or performances. The association between MMSE scores and automaticity index had the largest standardized β and variance explained across both DT difficulties, with or without controlling for demographics.

Table 2. Unadjusted regression models of different gait automaticity measures and MMSE (n=171).

Model	**R^2**	**Model F-statistics**	**Model p-value**	**Standardized β (Estimates ± SE)**	**β t-statistics**	**β p-value**
evenABC Task						
$\text{AutomaticityIndex}_{\text{evenABC}}$	0.06	9.97	0.002	-0.23 ± 0.07	-3.16	0.002
$\text{PFCActivation}_{\text{evenABC}}$	0.03	5.57	0.02	-0.18 ± 0.08	-2.36	0.02
$\Delta\text{Performance}_{\text{evenABC}}$	0.005	0.91	0.34	0.07±0.07	0.95	0.34
unevenABC Task						
$\text{AutomaticityIndex}_{\text{unevenABC}}$	0.05	9.11	0.003	-0.22 ± 0.07	-3.02	0.05
$\text{PFCActivation}_{\text{unevenABC}}$	0.02	3.07	0.08	-0.13 ± 0.08	-1.75	0.02

$\Delta Performance_{unevenABC}$	0.005	0.846	0.36	0.07±0.08	0.92	0.005

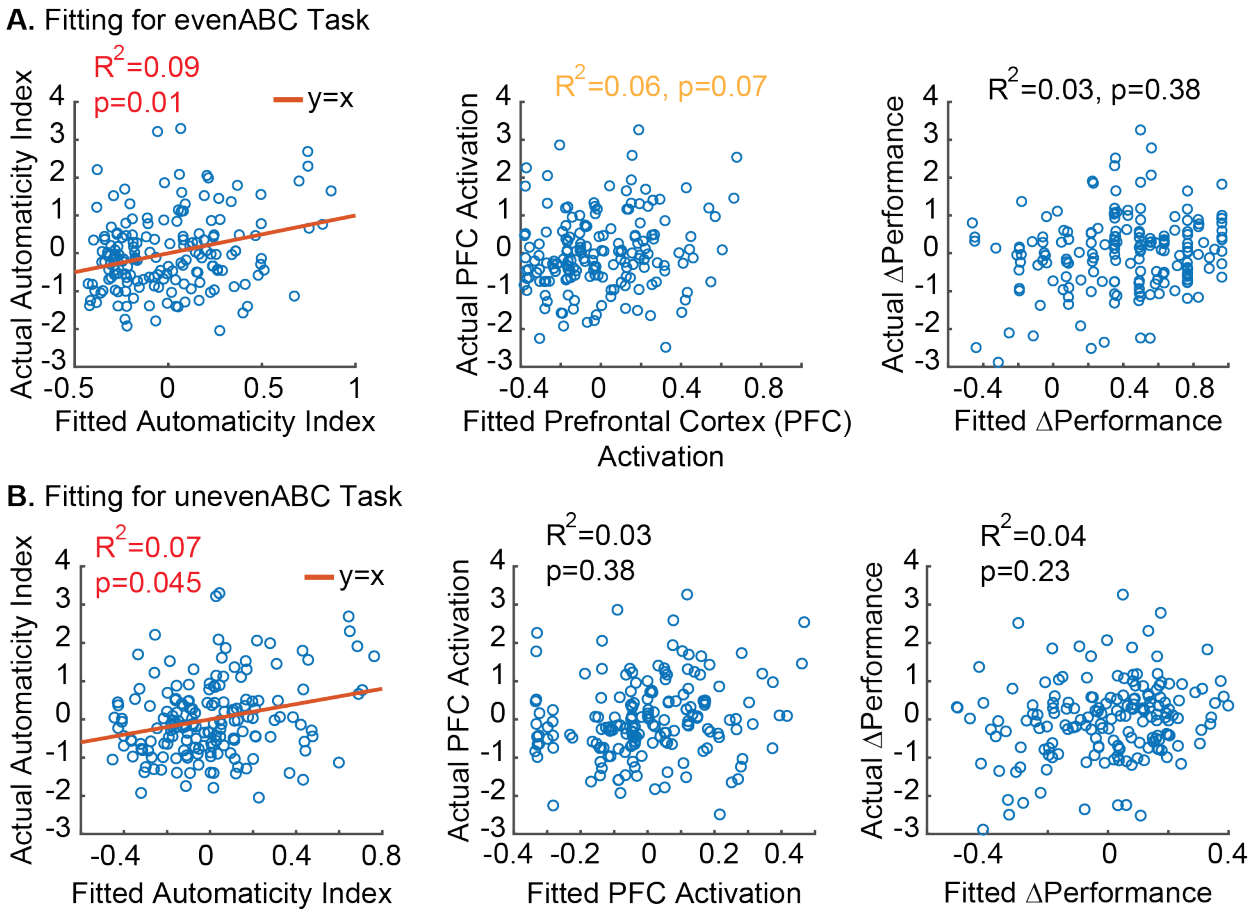

Figure 4. Model fitting between MMSE scores and automaticity index, $PFC_{Activations}$, and ΔPerformance after adjusting for age, sex, and highest level of education. Actual vs fitted value for each model in the evenABC task (A) and unevenABC task (B). Significant models are shown with a red line for y=x. A perfect fitting model would have actual and fitted values follow the y=x line. Only the associations between MMSE and automaticity index in both task difficulties were significant.

Table 3. Multivariable regression models of different metrics to quantify gait automaticity with MMSE (n=171) adjusted for age, sex, and highest level of education.

	R^2	Model F-statistics	Model p-value	Standardized β_1 (Estimates ± SE)	β_1 t-statistics	β_1 p-value
evenABC Task						
$AutomaticityIndex_{evenABC}$	0.09	3.09	0.01	-0.20±0.08	-2.60	0.01
$PFCActivation_{evenABC}$	0.03	2.11	0.07	-0.12±0.08	-1.59	0.11
$\Delta Performance_{evenABC}$	0.03	1.07	0.38	-0.12±0.08	1.54	0.13

unevenABC Task						
$AutomaticityIndex_{unevenABC}$	0.07	2.33	0.04	-0.17±0.08	-2.25	0.03
$PFCActivation_{unevenABC}$	0.03	1.07	0.38	-0.09±0.08	-1.12	0.26
$\Delta Performance_{unevenABC}$	0.04	1.38	0.23	0.11±0.08	1.37	0.17

Discussion

We combined measures of PFC activation and DT performance to create a monotonic index to quantify gait automaticity. We showed that the automaticity index better captures the task difficulty-related change in automaticity and is more strongly related to general cognitive function than either PFC activation or DT performance alone. In summary, the proposed index was effective at differentiating 1) between tasks, and 2) between subjects.

Task Performance contributes valuable information to the index when comparing task difficulties.

When comparing task difficulties, we expected the harder task to show worse automaticity; specifically, the more challenging task will require increased attentional demand from the PFC and decrease in performance due to greater interference between the motor and cognitive tasks. This change should be reflected as an increase in automaticity index, increase in PFC activation, and a decrease in performance. We observed 73% of participants increased automaticity index and 71% decreased performance as expected, but only 57% participants increased PFC activation from evenABC to unevenABC. The result confirms the unevenABC task was more challenging to the participants, as the majority of the participants decreased performance, but this increased challenge was not always reflected in PFC activation alone. This finding is consistent with previous studies showing that DT performance is related to older adults' mobility (Montero-Odasso et al., 2012; Verghese et al., 2012) and cognitive abilities (Brauner et al., 2021; Holtzer et al., 2006; Rosso et al., 2019). These observations highlight that performance contains crucial information when interpreting PFC activities.

It's not surprising that behavioral responses are more consistent than PFC activations because of the intrinsic heterogeneity in PFC response measured by fNIRS. fNIRS signals are noisier compared to performance measures as the signals can be impacted by physiological changes, skin properties etc. (Menant et al., 2020). Nevertheless, the engagement of attentional resources are signatures of reduced automaticity (Clark, 2015; Van Swearingen & Studenski, 2014). Performance alone does not quantify automaticity as automaticity is defined by good walking performance achieved with minimum neural inputs from the attentional and executive control center (Clark, 2015). Furthermore, most theoretical models emphasize the importance of examining the activation patterns of PFC to understand cognitive aging (Festini et al., 2018; Park & Reuter-Lorenz, 2009; Reuter-Lorenz & Cappell, 2008). Considering fNIRS is a relatively new technology with fast-evolving instrument design and analysis techniques (Perrey, 2014), future studies should keep considering performance and PFC activities together using the automaticity index to improve quantification of gait automaticity.

Poorer Automaticity index was related to lower general cognitive function.

When comparing across participants, we showed that lower cognitive function, measured by MMSE score, is related to lower automaticity index in both DT difficulties. The results suggest that the automaticity index was more sensitive to individual characteristics that could impact automaticity than PFC activations and performances, which are existing metrics to quantify automaticity.

However, we noticed that the variance explained by the models (R^2) is relatively low. The fit remains roughly the same with or without adjusting for age, sex, and highest level of education, suggesting that most of the variance in the automaticity index and PFC activity was not explained by the demographics and cognitive abilities. The low R^2 is not unexpected as gait automaticity depends on the subcortical circuits, which were not measured with fNIRS during walking (Clark, 2015; Rosano et al., 2007; Wu & Hallett, 2005). Thus, complementary imaging data about the integrity of the subcortical circuits, including volume or circuitry connectivity, might account for the unexplained variance in the model.

In our study, MMSE was not related to ΔPerformance. In comparison, a prior study (Brauner et al., 2021) has found that MMSE score is associated with ΔPerformance (Spearman's $\rho = 0.36$). Of note, ΔPerformance is a component in calculating the automaticity index, but we were not able to observe a direct association between MMSE score and ΔPerformance in our study. Several factors could contribute to this difference: 1) a different dual task paradigm was used; 2) the population recruited might be different. Specifically, the prior study had an older sample than we did (>= 85 years old vs mean 73.93 $\pm$ 5.65 in our sample).

Limitations

One main limitation is that the automaticity index can only be computed for study designs with at least two distinct task difficulties, because parameter optimization α requires at least two difficulties. Additionally, even though the proposed method to compute the automaticity index can be applied to any dual-task paradigm with at least two levels of task difficulties, the samples used to test the index all performed the same dual task walking paradigm (i.e., walking and reciting alternating letters of the alphabet with or without an uneven surface). It has been shown that dual task modality can impact performance and assessment results differently (Beurskens et al., 2014; Tsang et al., 2022). Therefore, it is important to verify that the metric is robust to varying task designs in future studies. Lastly, the samples recruited are relatively healthy in their cognitive abilities (MMSE mean $\pm$ SD: 28.42 $\pm$ 1.83, min = 21), which may not reflect the population of community dwelling older adults (Jacqmin-Gadda et al., 1997). Future studies can assess if the findings are generalizable to populations with a wider range of cognitive abilities.

Conclusions

We have addressed the need to better quantify gait automaticity using a novel approach to combine both DT performance and PFC activation into an automaticity index. We demonstrated the efficacy of the index by showing that it satisfied two objectives: better differentiation of automaticity 1) between tasks within subjects, and 2) between subjects. Specifically, the index revealed a decrease in automaticity as task difficulty increased that was not evidenced by PFC activation. Furthermore, the index captured the cognitive ability-related differences in automaticity better than PFC activation or DT performance alone, especially for the harder task difficulty. In summary, the automaticity index provides a standard metric to characterize gait automaticity. The index could

be an improved metric to quantify changes in automaticity from interventions and facilitate future studies to investigate the relationships between automaticity and other subject-specific characteristics.

Funding

This work was supported by NSF Career Award 14847891, Pittsburgh Pepper Center P30AG024827**,** RF1AG025516, K01 AG053431, R01-AG045252, K24AG057728, R01 AG057671, R01AG023651**,** U01AG061393

References

Aizenstein, H. J., Nebes, R. D., Saxton, J. A., Price, J. C., Mathis, C. A., Tsopelas, N. D., Ziolko, S. K., James, J. A., Snitz, B. E., Houck, P. R., Bi, W., Cohen, A. D., Lopresti, B. J., DeKosky, S. T., Halligan, E. M., & Klunk, W. E. (2008). Frequent Amyloid Deposition Without Significant Cognitive Impairment Among the Elderly. *Archives of Neurology*, *65*(11), 1509. https://doi.org/10.1001/archneur.65.11.1509

Beurskens, R., Helmich, I., Rein, R., & Bock, O. (2014). Age-related changes in prefrontal activity during walking in dual-task situations: A fNIRS study. *International Journal of Psychophysiology*, *92*(3), 122–128. https://doi.org/10.1016/j.ijpsycho.2014.03.005

Brach, J. S., VanSwearingen, J. M., Gil, A., Nadkarni, N. K., Kriska, A., Cham, R., & Perera, S. (2020). Program to improve mobility in aging (PRIMA) study: Methods and rationale of a task-oriented motor learning exercise program. *Contemporary Clinical Trials*, *89*, 105912. https://doi.org/10.1016/j.cct.2019.105912

Brandler, T. C., Oh-Park, M., Wang, C., Holtzer, R., & Verghese, J. (2012). Walking while talking: Investigation of alternate forms. *Gait and Posture*, *35*(1), 164–166. https://doi.org/10.1016/j.gaitpost.2011.08.003

Brauner, F. O., Balbinot, G., Figueiredo, A. I., Hausen, D. O., Schiavo, A., & Mestriner, R. G. (2021). The Performance Index Identifies Changes Across the Dual Task Timed Up and Go Test Phases and Impacts Task-Cost Estimation in the Oldest-Old. *Frontiers in Human Neuroscience*, *15*(September), 1–12. https://doi.org/10.3389/fnhum.2021.720719

Brustio, P. R., Rabaglietti, E., Formica, S., & Liubicich, M. E. (2018). Dual-task training in older adults: The effect of additional motor tasks on mobility performance. *Archives of Gerontology and Geriatrics*, *75*(September 2017), 119–124. https://doi.org/10.1016/j.archger.2017.12.003

Clark, D. J. (2015). Automaticity of walking: Functional significance, mechanisms, measurement and rehabilitation strategies. *Frontiers in Human Neuroscience*, *9*(MAY), 1–13. https://doi.org/10.3389/fnhum.2015.00246

Clark, D. J., Rose, D. K., Ring, S. A., & Porges, E. C. (2014). Utilization of central nervous system resources for preparation and performance of complex walking tasks in older adults. *Frontiers in Aging Neuroscience*, *6*(AUG), 1–9. https://doi.org/10.3389/fnagi.2014.00217

Festini, S. B., Zahodne, L., & Reuter-Lorenz, P. A. (2018). Theoretical Perspectives on Age Differences in Brain Activation: HAROLD, PASA, CRUNCH—How Do They STAC Up? *Oxford Research Encyclopedia of Psychology*, 1–24. https://doi.org/10.1093/acrefore/9780190236557.013.400

Fettrow, T., Hupfeld, K., Tays, G., Clark, D. J., Reuter-Lorenz, P. A., & Seidler, R. D. (2021). Brain activity during walking in older adults: Implications for compensatory versus dysfunctional accounts. *Neurobiology of Aging*, *105*, 349–364. https://doi.org/10.1016/j.neurobiolaging.2021.05.015

Folstein, M. F., Folstein, S. E., & McHugh, P. R. (1975). "Mini-mental state". A practical method for grading the cognitive state of patients for the clinician. *Journal of Psychiatric Research*, *12*(3), 189–198. https://doi.org/10.1016/0022-3956(75)90026-6

Ganguli, M., Chang, C.-C. H., Snitz, B. E., Saxton, J. A., Vanderbilt, J., & Lee, C.-W. (2010). Prevalence of Mild Cognitive Impairment by Multiple Classifications: The Monongahela-Youghiogheny Healthy Aging Team (MYHAT) Project. *The American Journal of Geriatric Psychiatry*, *18*(8), 674–683. https://doi.org/10.1097/JGP.0b013e3181cdee4f

Gschwind, Y. J., Bridenbaugh, S. A., & Kressig, R. W. (2010). Gait disorders and falls. *GeroPsych: The Journal of Gerontopsychology and Geriatric Psychiatry*, *23*(1), 21–32. https://doi.org/10.1024/1662-9647/a000004

Herold, F., Wiegel, P., Scholkmann, F., Thiers, A., Hamacher, D., & Schega, L. (2017). Functional near-infrared spectroscopy in movement science: a systematic review on cortical activity in postural and walking tasks. *Neurophotonics*, *4*(4), 041403. https://doi.org/10.1117/1.nph.4.4.041403

Holtzer, R., Mahoney, J. R., Izzetoglu, M., Izzetoglu, K., Onaral, B., & Verghese, J. (2011). fNIRS study of walking and walking while talking in young and old individuals. *Journals of Gerontology - Series A Biological Sciences and Medical Sciences*, *66 A*(8), 879–887. https://doi.org/10.1093/gerona/glr068

Holtzer, R., Verghese, J., Xue, X., & Lipton, R. B. (2006). Cognitive processes related to gait velocity: Results from the Einstein aging study. *Neuropsychology*, *20*(2), 215–223. https://doi.org/10.1037/0894-4105.20.2.215

Hoppes, C. W., Huppert, T. J., Whitney, S. L., Dunlap, P. M., Disalvio, N. L., Alshebber, K. M., Furman, J. M., Kwon, Y. H., & Rosso, A. L. (2020). Changes in Cortical Activation during Dual-Task Walking in Individuals with and without Visual Vertigo. *Journal of Neurologic Physical Therapy*, *44*(2), 156–163. https://doi.org/10.1097/NPT.0000000000000310

Jacqmin-Gadda, H., Fabrigoule, C., Commenges, D., & Dartigues, J. F. (1997). A 5-year longitudinal study of the mini-mental state examination in normal aging. *American Journal of Epidemiology*, *145*(6), 498–506. https://doi.org/10.1093/oxfordjournals.aje.a009137

Laguë-Beauvais, M., Fraser, S. A., Desjardins-Crépeau, L., Castonguay, N., Desjardins, M., Lesage, F., & Bherer, L. (2015). Shedding light on the effect of priority instructions during dual-task performance in younger and older adults: A fNIRS study. *Brain and Cognition*, *98*, 1–14. https://doi.org/10.1016/j.bandc.2015.05.001

Leys, C., Ley, C., Klein, O., Bernard, P., & Licata, L. (2013). Detecting outliers: Do not use standard deviation around the mean, use absolute deviation around the median. *Journal of Experimental Social Psychology*, *49*(4), 764–766. https://doi.org/10.1016/j.jesp.2013.03.013

Longhurst, J. K., Rider, J. V., Cummings, J. L., John, S. E., Poston, B., Held Bradford, E. C., & Landers, M. R. (2022). A Novel Way of Measuring Dual-Task Interference: The Reliability and Construct Validity of the Dual-Task Effect Battery in

Neurodegenerative Disease. *Neurorehabilitation and Neural Repair*, *36*(6), 346–359. https://doi.org/10.1177/15459683221088864

Maillet, D., & Rajah, M. N. (2013). Association between prefrontal activity and volume change in prefrontal and medial temporal lobes in aging and dementia: A review. *Ageing Research Reviews*, *12*(2), 479–489. https://doi.org/10.1016/j.arr.2012.11.001

Menant, J. C., Maidan, I., Alcock, L., Al-Yahya, E., Cerasa, A., Clark, D. J., de Bruin, E., 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., … Mirelman, A. (2020). A consensus guide to using functional near-infrared spectroscopy in posture and gait research. *Gait and Posture*, *82*(May), 254–265. https://doi.org/10.1016/j.gaitpost.2020.09.012

Miyai, I., Tanabe, H. C., Sase, I., Eda, H., Oda, I., Konishi, I., Tsunazawa, Y., Suzuki, T., Yanagida, T., & Kubota, K. (2001). Cortical mapping of gait in humans: A near-infrared spectroscopic topography study. *NeuroImage*, *14*(5), 1186–1192. https://doi.org/10.1006/nimg.2001.0905

Montero-Odasso, M., Muir, S. W., Hall, M., Doherty, T. J., Kloseck, M., Beauchet, O., & Speechley, M. (2011). Gait variability is associated with frailty in community-dwelling older adults. *Journals of Gerontology - Series A Biological Sciences and Medical Sciences*, *66 A*(5), 568–576. https://doi.org/10.1093/gerona/glr007

Montero-Odasso, M., Verghese, J., Beauchet, O., & Hausdorff, J. M. (2012). Gait and cognition: A complementary approach to understanding brain function and the risk of falling. *Journal of the American Geriatrics Society*, *60*(11), 2127–2136. https://doi.org/10.1111/j.1532-5415.2012.04209.x

Park, D. C., & Reuter-Lorenz, P. (2009). The adaptive brain: Aging and neurocognitive scaffolding. *Annual Review of Psychology*, *60*, 173–196. https://doi.org/10.1146/annurev.psych.59.103006.093656

Patla, A. E., & Shumway-Cook, A. (1999). Dimensions of Mobility: Defining the Complexity and Difficulty Associated with Community Mobility. *Journal of Aging and Physical Activity*, *7*(1), 7–19. https://doi.org/10.1123/japa.7.1.7

Paul, S. S., Ada, L., & Canning, C. G. (2005). Automaticity of walking–implications for physiotherapy practice. *Physical Therapy Reviews*, *10*(1), 15–23. https://doi.org/10.1179/108331905X43463

Perrey, S. (2014). Possibilities for examining the neural control of gait in humans with fNIRS. *Frontiers in Physiology*, *5 MAY*(May), 10–13. https://doi.org/10.3389/fphys.2014.00204

Rantakokko, M., Portegijs, E., Viljanen, A., Iwarsson, S., Kauppinen, M., & Rantanen, T. (2016). Changes in life-space mobility and quality of life among community-dwelling older people: a 2-year follow-up study. *Quality of Life Research*, *25*(5), 1189–1197. https://doi.org/10.1007/s11136-015-1137-x

Reuter-Lorenz, P. A., & Cappell, K. A. (2008). Neurocognitive aging and the compensation hypothesis. *Current Directions in Psychological Science*, *17*(3), 177–182. https://doi.org/10.1111/j.1467-8721.2008.00570.x

Rosano, C., Aizenstein, H. J., Studenski, S., & Newman, A. B. (2007). A regions-of-interest volumetric analysis of mobility limitations in community-dwelling older adults. *Journals of Gerontology - Series A Biological Sciences and Medical Sciences*, *62*(9), 1048–1055. https://doi.org/10.1093/gerona/62.9.1048

Rosso, A. L., Metti, A. L., Faulkner, K., Redfern, M., Yaffe, K., Launer, L., Elizabeth Shaaban, C., Nadkarni, N. K., & Rosano, C. (2019). Complex Walking Tasks and Risk for Cognitive Decline in High Functioning Older Adults. *Journal of Alzheimer's Disease*, *71*(s1), S65–S73. https://doi.org/10.3233/JAD-181140

Rosso, A. L., Taylor, J. A., Tabb, L. P., & Michael, Y. L. (2013). Mobility, disability, and social engagement in older adults. *Journal of Aging and Health*, *25*(4), 617–637. https://doi.org/10.1177/0898264313482489

Santosa, H., Zhai, X., Fishburn, F., & Huppert, T. (2018). The NIRS Brain AnalyzIR toolbox. *Algorithms*, *11*(5). https://doi.org/10.3390/A11050073

Sheppard, K. D., Sawyer, P., Ritchie, C. S., Allman, R. M., & Brown, C. J. (2013). Life-space mobility predicts nursing home admission over 6 years. *Journal of Aging and Health*, *25*(6), 907–920. https://doi.org/10.1177/0898264313497507

Thies, S. B., Richardson, J. K., DeMott, T., & Ashton-Miller, J. A. (2005). Influence of an irregular surface and low light on the step variability of patients with peripheral neuropathy during level gait. *Gait and Posture*, *22*(1), 40–45. https://doi.org/10.1016/j.gaitpost.2004.06.006

Tsang, C. S. L., Wang, S., Miller, T., & Pang, M. Y. C. (2022). Degree and pattern of dual-task interference during walking vary with component tasks in people after stroke: a systematic review. *Journal of Physiotherapy*, *68*(1), 26–36. https://doi.org/10.1016/j.jphys.2021.12.009

Van Swearingen, J. M., & Studenski, S. A. (2014). Aging, motor skill, and the energy cost of walking: Implications for the prevention and treatment of mobility decline in older persons. *Journals of Gerontology - Series A Biological Sciences and Medical Sciences*, *69*(11), 1429–1436. https://doi.org/10.1093/gerona/glu153

Verghese, J., Holtzer, R., Lipton, R. B., & Wang, C. (2012). Mobility stress test approach to predicting frailty, disability, and mortality in high-functioning older adults. *Journal of the American Geriatrics Society*, *60*(10), 1901–1905. https://doi.org/10.1111/j.1532-5415.2012.04145.x

Verghese, J., Kuslansky, G., Holtzer, R., Katz, M., Xue, X., Buschke, H., & Pahor, M. (2007). Walking While Talking: Effect of Task Prioritization in the Elderly. *Archives of Physical Medicine and Rehabilitation*, *88*(1), 50–53. https://doi.org/10.1016/j.apmr.2006.10.007

Wu, T., & Hallett, M. (2005). The influence of normal human ageing on automatic movements. *The Journal of Physiology*, *562*(2), 605–615. https://doi.org/10.1113/jphysiol.2004.076042

Yogev-Seligmann, G., Rotem-Galili, Y., Mirelman, A., Dickstein, R., Giladi, N., & Hausdorff, J. M. (2010). How does explicit prioritization alter walking during dual-task performance? Effects of age and sex on gait speed and variability. *Physical Therapy*, *90*(2), 177–186. https://doi.org/10.2522/ptj.20090043