Gait Analysis with an Integrated Mobile Robot and Wearable Sensor System Reveals Associations Between Cognitive Ability and Dynamic Balance in Older Adults

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Abstract— **Gait abnormalities and postural instability have been linked to cognitive decline in older adults, however the causal relationships between cognitive capacity and gait is still an open problem. Emerging portable technologies may help elucidate these connections by enabling gait analysis in out-of-the-lab settings, with higher sensitivity than timed gait assessment tests. The purpose of this work was to evaluate the associations between cognitive ability (Montreal Cognitive Assessment scores) and measures of gait and balance disturbance (spatiotemporal gait parameters, dynamic margin of stability) in a group of older adults, under a dual-task walking paradigm, using an integrated gait analysis system that features a mobile robot and in-shoe sensors. Results of hierarchical regression analyses adjusted for age and gender indicated that decline in cognitive ability in older adults is independently associated with more conservative overground gait patterns (i.e., smaller absolute values of the anteroposterior margin of stability) and increased gait variability (i.e., larger coefficients of variation in stride time and stride velocity) when performing dual-task walking. These results provide proof-of-concept validation of the applicability of integrated robotic and wearable sensors technologies to out-of-the-lab gait analysis in older adults.**

Index Terms— **Wearable Technology, Instrumented Footwear, Assistive Robots, Ambulatory Gait Analysis, Dynamic Margin of Stability.**

I. Introduction

Independent mobility is an essential indicator of physical health status and a predictor of fall risk [1] and cognitive function [2] in older individuals. A growing body of research has shown that poor walking performance correlates with cognitive impairment in older adults [2], [3]. In these studies, the dual-task paradigm, which requires individuals to walk while performing a secondary cognitive task, has often been used to investigate associations between gait and cognitive impairment [4]. Several clinical tools are available to assess physical and cognitive functions in older adults. Among these, the Short Physical Performance Battery (SPPB) has been identified as a reliable and persistent predictor of functional deterioration [1], [5]. The Montreal Cognitive Assessment (MoCA) is a highly sensitive cognitive impairment assessment tool [6] that has shown positive correlation with SPPB scores [7] and negative correlation with gait impairments and fall risk [8]. However, the common mechanisms underlying the relationship between motor performance and cognitive ability are still not well understood. The emerging gait and balance monitoring technologies may help elucidate these mechanisms by enabling more accessible, sensitive, and objective measurements in out-of-the lab settings.

Several research groups have proposed mobile robots equipped with vision-based sensors (i.e., infrared, depth, and RGB cameras) as tools for gait analysis and monitoring [9]. RGB-D cameras offer real-time three-dimensional tracking of the human body, while the mobility of the robotic platform compensates for the limited field of view of the RGB-D cameras. In [10], an RGB-D sensor was fitted on a mobile robot to monitor an individual's 3D body motion and assess their gait while they navigated in a pre-mapped environment. The authors of [11] proposed a robotic system to analyze gait patterns in clinical environments. Their system comprises a mobile robot equipped with RGB-D sensors for monitoring human motion and a LIDAR sensor for mapping and localization. In [12], an on-board laser scanner was added to the RGB-D sensors to increase the robustness of the robot motion tracking capabilities for individuals that used mobility aids, such as walkers and crutches.

To enhance the quality of life in older adults, it is critical to develop new tools that can automatically detect the onset of cognitive decline, thereby allowing early interventions [13]. Inertial measurement units (IMUs) are increasingly being used to capture gait patterns that may predict future dementia [14]. A study that relied on shank-attached IMUs showed that spatial and temporal gait parameters in older adults are predictive of cognitive decline at two-year follow up [15].

Fusing data from multiple diverse sensors holds significant potential for gait analysis [16], [17]. Yet, no research to date has investigated associations between motor and cognitive functions using an integrated robot and wearable sensor system. The objective of this study is to investigate associations between cognitive ability and measures of gait and balance disturbance (namely, spatiotemporal gait parameters and dynamic margin of stability (MoS) in the sagittal and frontal planes) in community dwelling older adults during

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Fig. 1. Integrated robot and wearable sensor system used to administer walking tests to older adults in a senior center.

overground walking tasks, using a dual-task paradigm. To the best of the authors' knowledge, this is the first study analyzing associations between cognitive ability and measures of dynamic stability during overground walking. This capability is enabled by an integrated robot and wearable sensor system recently developed by our team, which was previously validated in a laboratory environment with healthy adults [18], [19]. This paper builds upon our previous studies and provides an investigation of how a clinical measure of cognitive function (MoCA scores) is associated with changes in gait and balance metrics captured by the integrated system during dual-task walking in older adults. Furthermore, to assess clinical feasibility of the technology, we explored associations between the same gait metrics and a standardized clinical motor function assessment (SPPB).

The rest of the paper is organized as follows: Section II provides an overview of the integrated robot and wearable sensor system. Section III summarizes the methods we applied to estimate spatiotemporal gait parameters and margin of stability from the robot and wearable sensors data. Section IV describes the experimental protocol and Section V illustrates the multivariate regression models used to investigate associations between clinical scores (MoCA or SPPB) and gait parameters. Section VI presents the results of the analysis. Lastly, the paper is concluded in Section VII.

II. System Description

The mobile robot system (Fig. 1, top) consists of a P3-DX differential drive robot, an Azure Kinect sensor, a Kinect v1 sensor, and a laptop [18]. The Azure Kinect sensor facing backward captures an individual's lower-body movements. The poses of the pelvis and ankle joints are recorded in the Azure Kinect sensor frame and then transformed to the world coordinate frame. This allows the robot to precede the test subject at a constant distance of approximately 1.5 m while monitoring their gait. The Kinect v1 sensor facing forward is utilized to map the environment and estimate the current position of the P3-DX robot. The laptop computer is located on the robot and is responsible for data acquisition and processing using the methods described in Sec. III. The wearable sensor system (Fig. 1, bottom) consists of insoles instrumented with a nine degree-of-freedom IMU and a eight-cell array of force-sensitive resistors (FSRs) [20]. Each insole is connected to a logic unit that is attached to the postero-lateral side of the wearer's own shoes. The logic units are used to gather data from the insole sensors. The raw signals are sent to the robot laptop at 270 Hz via UDP and converted into clinically relevant gait parameters in real time, as described in the following section.

III. Estimation of Gait Parameters

A. Spatiotemporal Gait Parameters

Temporal gait parameters are extracted from FSR signals. Instances of heel strike (HS) and toe-off (TO) are detected when the sum of the FSR signals underneath the hindfoot and forefoot exceeds or drop below a fixed threshold. The time interval during which the normalized acceleration of the foot (as estimated by the insole-embedded IMU) lies below an empirically-determined threshold is used to detect the foot-flat phase (FF) of each gait cycle. Stride time (ST) is defined as the time interval between two successive HS of the same foot. Swing time is computed as the time interval between TO and the following HS of the same foot. Swing percent (SWP) is calculated as the ratio of swing time over ST. The system calculates spatial gait parameters from the position of the IMUs during the FF. The IMU positions at FF are first measured in the Azure Kinect frame and then mapped to the world frame using the robot localization capability. The distance between two consecutive IMU positions of the same foot at FF yields the stride length (SL). Stride velocity (SV) is calculated as the ratio of SL over ST. More details about the spatiotemporal gait parameters estimation can be found in [18], [20].

B. Dynamic Margin of Stability

Dynamic margin of stability (MoS) is a common measure to quantify an individual's ability to maintain balance during walking. The MoS extends the condition of static stability to dynamic conditions, by accounting for the velocity of the body center of mass [21]. The MoS is defined as the distance between the extrapolated center of mass (XCoM, denoted $\boldsymbol{\xi}$), and the base of support (BoS). The XCoM is determined by adding to the vertical projection of center of mass (CoM, denoted $\boldsymbol{r}$) a term that is proportional to the CoM velocity $\dot{\boldsymbol{r}}$, as described by

$$\boldsymbol{\xi} = \boldsymbol{r} + \frac{\dot{\boldsymbol{r}}}{\omega_0}, \tag{1}$$

where ω_0 is the natural frequency

$$\omega_0 = \sqrt{\frac{g}{l}} \tag{2}$$

and g, l are the gravity acceleration and the average height of the CoM in the sagittal plane, respectively.

To estimate the MoS, we fuse the data from the robot and wearable sensors. The Azure Kinect sensor is used to track the pelvis and foot poses. We transform these poses

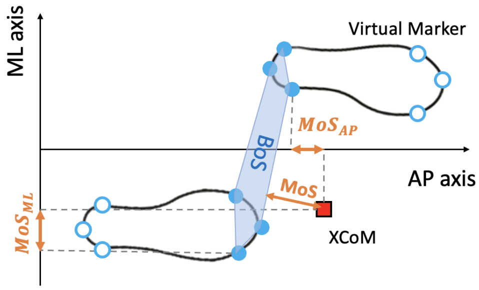

Fig. 2. Definition of MoS, MoS_{AP}, and MoS_{ML} given the locations of 12 virtual markers (filled and un-filled black circles) tracked by the robotic system. Filled circles delimit segments of the feet that are in contact with the ground, which are used to determine the BoS.

from the Kinect frame to the world frame using the robot location. The foot pose estimates are refined by an Extended Kalman Filter (EKF) that fuses the raw measurements by the Kinect sensor with the linear acceleration and angular velocity of the corresponding foot measured by the insole IMU. To determine the BoS from the estimated foot poses, 6 virtual markers are placed on the geometric boundary of each foot, with 3 markers representing the forefoot and 3 markers representing the hindfoot segments (Fig. 2). At each timestamp, we consider the subset of the 12 virtual markers corresponding to the foot segments that are currently in contact with the ground, as indicated by the FSRs readings. The BoS is estimated as the convex hull of this subset of virtual markers. Furthermore, the current foot pose estimates and the FSR readings determine the Center of Pressure (CoP), which is used by a second EKF to estimate the CoM velocity $\dot{\boldsymbol{r}}$. This EKF also improves the accuracy of the raw CoM approximated by the pelvis pose measurements made by the robot sensors, thereby providing a more accurate estimate of XCoM via (1). With the BoS and XCoM available, the MoS is calculated at each timestamp as the signed distance between the BoS and XCoM (positive if the XCoM lies inside the BoS, and negative otherwise). The MoS time series is then projected onto the AP and ML axes[1] and the following 3 scalars are extracted at each gait cycle: MoS_{AP} is the mean of the AP projection of the MoS measured over the gait cycle; $\text{MoS}_{\text{ML,pos}}$ and $\text{MoS}_{\text{ML,neg}}$ are the positive and negative ML projections of the MoS integrated over the gait cycle, respectively. More details about the MoS estimation can be found in [19].

IV. Experimental Protocol

Twenty-four community dwelling individuals aged 65 and older (Tab. I) were recruited from a community center in Queens (New York City, NY). The study was approved by the IRBs of Columbia University and Stevens Institute of Technology, and all participants provided written informed consent.

All experiments took place in a common area within the community center. An oval path, approximately 38-meter long, was marked on the floor with adhesive tape to serve as the nominal path for all the walking trials (Fig. 3). First, two trained research staff administered the MoCA and the SPPB tests. The MoCA was selected given its high sensitivity and low ceiling effects for individuals with mild cognitive impairments [26]. The SPPB examines balance, lower extremity muscular capacity, and mobility, and has been widely used as an accurate and reliable assessment of physical function [27]. Afterwards, each participant completed 2 laps along the oval path, at their preferred pace (familiarization trial, FS). The goal of FS was to get the subjects accustomed to walking with the instrumented insoles while the mobile robot preceded them. After the FS, each participant completed 2 additional walking trials, each consisting of 4 laps along the same oval path, while their gait was monitored by the integrated robot/insole system. One trial required subjects to walk at their preferred pace (normal walking, N), the other one included a secondary cognitive task (dual-task walking, D). The cognitive task required the study participants to count backwards by 3, starting from a random number. Both the sequence of the trials (N, D) and the walking direction (clockwise, counterclockwise) were assigned to participants using a Latin square design.

V. Statistical Analysis

We analyzed 3 groups of gait parameters: i) mean and coefficient of variation (CV) of SL, SV, ST, SWP, MoS_{AP},

TABLE I
Demographic Information, MoCA Scores, SPPB Scores

Age, mean (SD)	75.8 (5.4)
Sex, n (%)	
Male	8 (33.3%)
Female	16 (66.7%)
BMI [kg/m^2], mean (SD)	26.13 (4.18)
Height [m], mean (SD)	1.61 (0.07)
Weight [kg], mean (SD)	67.5 (12.5)
Gait speed [m/s] (SD)	0.98 (0.19)
Normal ($\geq$ 1 m/s) [22]	54.17%
Risk for adverse events (0.6-0.8 m/s) [23]	12.50%
Impaired individuals ($\leq$ 0.6 m/s) [23]	4.17%
MoCA (0-30), mean (SD)	21.5 (3.6)
Cognitive impairment ($\leq$ 26) [24]	100%
SPPB (0-12), mean (SD)	8.3 (1.5)
Risk for disability (<10) [25]	75%

BMI: Body mass index; SD: Standard Deviation; MoCA: Montreal Cognitive Assessment; SPPB: Short Physical Performance Battery.

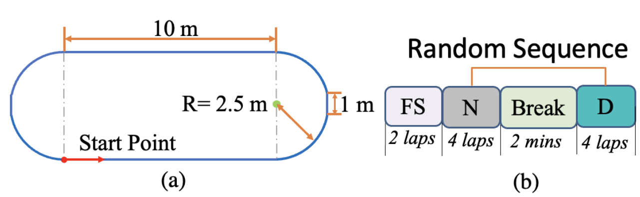

Fig. 3. Oval path used for the walking trials **(a)** and illustration of the experimental protocol **(b)**. N and D indicate normal and dual-task walking, respectively.

[1] The AP axis was estimated, stride by stride, from the segment connecting the location of the most recent HS to the previous HS of the ipsilateral foot.

TABLE II
SUMMARY GAIT PARAMETERS FOR N AND D TRIALS

	N		D	
	Mean	SD	Mean	SD
ST				
Mean [s]	1.17	0.14	1.20	0.15
CV (%)	3.72	1.14	3.91	2.04
SWP				
Mean (%GC)	35.11	2.79	34.78	2.46
CV (%)	6.12	5.09	6.87	5.12
SL				
Mean [m]	1.13	0.14	1.10	0.15
CV (%)	5.97	2.28	6.00	1.72
SV				
Mean [m/s]	0.98	0.20	0.94	0.2
CV (%)	7.44	2.6	7.77	3.29
MoS_{AP}				
Mean [m]	-0.151	0.072	-0.128	0.072
$MoS_{ML,pos}$				
Mean [m]	0.026	0.009	0.027	0.010
$MoS_{ML,neg}$				
Mean [m]	-0.022	0.012	-0.024	0.016

SD: Standard Deviation; CV: Coefficient of Variation; N: Normal walking; D: Dual-task walking.

$MoS_{ML,pos}$, and $MoS_{ML,neg}$, separately for trials N and D; ii) differences of the mean and CV values of each gait parameter between the two trials (i.e., $D-N$); iii) ratio of the mean and CV values of each gait parameter between the two trials (i.e., D/N). We applied hierarchical linear regression to examine whether SPPB and MoCA scores could predict the aforementioned gait metrics, after statistically adjusting for the effects of age and gender. To this end, for each gait parameter we fitted separate linear regression models, first by introducing age and gender as predictors (base model), then by adding either SPPB or MoCA scores (complete models). Age and gender were added as predictors in the base model because spatiotemporal parameters and dynamic MoS are age-related and sex-specific variables [28]. If there was a significant ($\alpha = 0.05$) increase in the proportion of variation explained by the complete models for a given gait parameter, we concluded that SPPB (or MoCA) scores were independently associated with that parameter. The assumption of normal distribution for the residuals was verified by reviewing the standardized residuals' normal probability plots. We further checked for deviations from linearity and homoscedasticity by evaluating the scatterplots of the standardized residuals plotted against the standardized expected values. SPSS v28 (IBM Corporation, Armonk, NY) was used to perform all analyses.

VI. RESULTS

Table II summarizes mean and CV of the gait parameters for normal walking (trial N) and dual-task walking (trial D). Table III shows the coefficients of determination (R^2) of the base and complete models, along with their difference (ΔR^2). Unstandardized regression coefficients (B) are reported for the clinical scores. Standardized coefficients (β) are included for all predictors in each complete model. For the sake of brevity, only the complete models resulting in significant ΔR^2 are included in the table.

The analysis evidenced that SPPB is positively associated with SL and negatively associated with MoS_{AP}. Additionally, MoCA scores were found to be independently associated with changes in ST and SV variability between trials N and D, and with the D/N ratio of MoS_{AP}. It is worth noting that β_{SPPB} and β_{MoCA} were larger than β_{age} and β_{gender} in all the significant models, indicating that the predictive ability of SPPB and MoCA are stronger than those of age and gender.

Figure 4 shows the partial regression plots for age, gender, and MoCA scores for all significant models. The angular coefficients of these lines represent the unstandardized regression coefficients of each predictor (age, gender, MoCA scores). From these plots, it can be inferred that the variability accounted for by the MoCA scores in each of the three models exceeded that of age and gender.

VII. DISCUSSION AND CONCLUSION

This paper is the first work reporting associations between MoCA scores, a measure of cognitive ability, and MoS, a measure of dynamic stability, in older adults during *overground* walking tasks. To achieve this goal, we used an integrated robot and wearable sensor system recently developed by our group. While the MoS has been widely used to study dynamic balance in older adults and other populations [29], only few studies [30]–[32] have applied the MoS to overground walking tasks, which more closely resemble real-life walking.

Our analysis indicated that SPPB and MoCA are associated with distinct gait domains. The positive association between SPPB and SL is in line with previous research [33] and further underscores the role of SPPB as a valid measure of mobility and physical function in older adults. Knee extensor muscles contribute to SL [34] and SPPB evaluates strength in these muscles through the five times sit-to-stand component of the assessment [35]. Additionally, static balance performance, which SPPB evaluates through three standing balance sub-tests, is known to be positively correlated with SL [36]. Thus, both associations can explain the correlation between SPPB and SL. The negative association between SBBP and MoS_{AP} was possibly mediated by SL, since MoS_{AP} is known to decrease as SL increases [37]. Interestingly, SPPB was not associated with SV, even though one component of the SPPB compound score specifically targets gait speed. One possible explanation is that SPPB determines preferred walking speed by relying on a short (3 or 4 m) walking test, whereas in our tests SV was computed as the average gait speed over a 150-meter walking bout. Hence, the estimates of SV were likely affected by fatigue.

In our sample, older adults with lower levels of cognitive impairment showed smaller increases in gait variability and less pronounced AP adaptations when performing a secondary cognitive task. Associations between increased stride-to-stride fluctuations in gait parameters and cognitive decline have been consistently reported in the literature [38]. Such associations have been linked to shared brain networks for gait control and cognition, which are challenged by dual-task walking [39]. Furthermore, a smaller ratio of MoS_{AP} between

TABLE III

MULTIPLE REGRESSION MODELS

		R^2_{M1}	R^2_{M12}	ΔR^2	B_{SPPB}	(95%CI)	β_{age}	β_{gender}	β_{SPPB}
MEAN	SL_N	0.115	$^{b}0.429$	$^{b}0.314$	$^{b}0.057$	(0.020,0.094)	0.009	-0.202	0.609
	SL_D	0.218	$^{b}0.516$	$^{b}0.298$	$^{b}0.057$	(0.022, 0.092)	-0.199	-0.096	0.593
	$\mathrm{MoS_{AP}}$_N	0.034	$^{a}0.276$	$^{a}0.242$	$^{a}-0.224$	(-0.046, -0.002)	-1.116	0.169	-0.521
	$\mathrm{MoS_{AP}}$_D	0.095	$^{a}0.340$	$^{a}0.244$	$^{a}-0.025$	(-0.045,-0.005)	-0.083	0.252	-0.537
		R^2_{M1}	R^2_{M2}	ΔR^2	B_{MoCA}	(95%CI)	β_{age}	β_{gender}	β_{MoCA}
CV	ST_(D-N)	0.014	$^{a}0.230$	$^{a}0.215$	$^{a}-0.273$	(-0.520,-0.025)	-0.255	0.192	-0.499
	SV_(D-N)	0.003	$^{a}0.208$	$^{a}0.205$	$^{a}-0.588$	(-1.142, -0.033)	-0.132	0.031	-0.487
MEAN	$\mathrm{MoS_{AP}}$_(D/N)	0.244	$^{a}0.491$	$^{a}0.247$	$^{a}0.228$	(0.055, 0.402)	-0.281	0.028	0.544

R^2_{M1} and R^2_{M2} are the coefficients of determination for the base models (age, gender) and for the complete models (age, gender, SPPB or MoCA), respectively. ΔR^2 is defined as $\left(R^2_{M2} - R^2_{M1}\right)$. The unstandardized regression coefficients B_{SPPB} and B_{MoCA} are reported along with their 95% confidence intervals (CI). β indicates the standardized regression coefficients for each predictor in the complete models. Suffixes N and D indicate normal and dual-task walking, respectively. Note: $^{a}p < 0.05$, $^{b}p < 0.01$,$^{c}p < 0.001$.

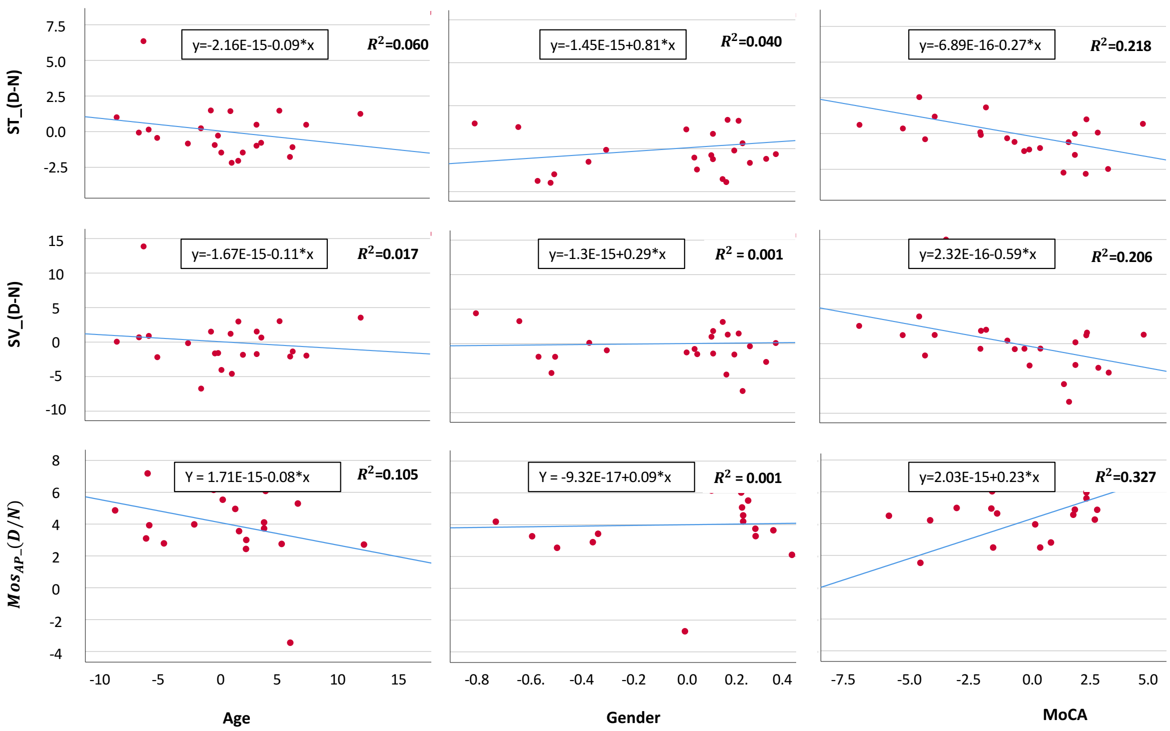

Fig. 4. Partial regression plots for the gait parameters showing significant associations with MoCA scores. The x axes represent the residuals from regressing the omitted predictor against the remaining predictors in the model. The y axes represent the residuals from regressing a gait parameter against all the predictors but one (age, gender or MoCA scores)

fast and preferred gait speed is an indicator of conservative gait strategies in older adults at risk of falling [30]. Similarly, our results on the D/N ratio of $\mathrm{MoS_{AP}}$ suggest that older adults with higher levels of cognitive impairment tend to show more marked AP adaptations toward conservative gait patterns when performing a secondary cognitive task.

One limitation of this study is the small sample size. Additionally, because the participants' performances in the cognitive task were not quantified, it was impossible to investigate potential mediating effects of task prioritization on the gait patterns measured during the dual-task condition [40]. Future work will include using the integrated system to assess longitudinal changes in gait and dynamic balance of older adults and those with neurological disorders following a rehabilitation program.

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