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Original Article

Assessment of dual-tasking during a dynamic balance task using a smartphone app: a pilot study

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Abstract. [Purpose] To assess if the instrumented Timed Up and Go (iTUG) task score calculated with an iPhone application can detect gait changes under dual-tasking conditions. [Participants and Methods] Twenty participants (age 38.30 ± 12.54 , 12 females) were asked to complete the TUG as a single task and under two dual-tasking conditions: 1) verbal fluency and 2) mental calculation. We used a smartphone, stopwatch, digital camera, and wearable sensor to calculate the dependent variables which included time, step count, gait speed, and iTUG score and, the dual-tasking cost (DTC) of those variables. We used Friedman analyses of variance and Wilcoxon tests for statistical analyses. [Results] the iTUG score, step count, gait speed, and the time measured by the stopwatch and wearable sensor differed significantly for all tasks, but the smartphone time did not. [Conclusion] We conclude that the iTUG score could be used as a sensitive measure for identifying gait changes under dual-tasking conditions. With the growing demands of telehealth, using technology as an objective tool for movement analysis is needed for clinicians and payers. Our findings demonstrate the potential value of the iTUG score to assess and track patient's progress. Key words: Dual-tasking, Smartphone, Gait

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INTRODUCTION

In the United States, smartphone use increased from 35% of the population in 2011 to 81% in 2019¹). The number and use of smartphone health applications in the rehabilitation field are also growing²⁾. Due to their easy access and low cost compared to three-dimensional (3D) motion capture systems, there is a potential for using smartphone applications to facilitate functional assessment for clinicians who lack access or expertise to use expensive assessment equipment. Additionally, with the growing demands for telehealth, the development of objective methods for movement analysis is needed for clinicians and payers³⁾. Smartphone applications could allow for quick and easy screening at more regular intervals to identify and document patient progress at home, minimizing the need to visit the clinic and providing the opportunity for more timely and effective treatment, as needed.

The Timed Up and Go (TUG) test is a clinical tool that assesses mobility⁴). Since it has limited ability for identifying those at high risk of falling⁵, researchers have attempted to increase the TUG's sensitivity for functional abnormalities^{6, 7}. For instance, the instrumented TUG test (iTUG) that uses Inertial Measurement Units (IMUs) is recommended for detailed gait and movement analyses⁷). Still, it is not a practical or affordable solution for clinicians who lack IMU expertise or the equipment. Another way to increase the TUG's sensitivity is by shifting to a dual-tasking paradigm⁶. However, not all secondary tasks impose similar effects on gait and posture. For instance, testing verbal fluency (VF) or mental calculation (MCT) interferes with brain areas that control gait⁵⁾ and can impact gait more negatively than tests that create external interference

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and depend on an external stimulus, such as a time reaction task^{5, 8–10)}. Therefore, VF and MCT tasks are commonly used simultaneously with the TUG to quantify the dual-tasking interference^{8, 11)} and have been shown to increase its sensitivity in identifying the fall risk¹²⁾.

A new way to score the iTUG task based on a smartphone application was recently recommended for evaluating gait changes in a neurological population¹³). This score considers both the time taken to complete the TUG and the 95% confidence ellipsoid (CE) volume that tracks changes in 3D acceleration¹³). However, adopting the iTUG score in clinical practice necessitates testing its feasibility in various typical day-to-day scenarios. For example, testing can determine if it can identify gait changes in healthy individuals, such as during dual-tasking conditions^{8–11}).

In this study, we assess the feasibility of using the iTUG score in identifying gait changes caused by dual-tasking. We elect to use healthy adults to eliminate the age factor and minimize the variability of dual-tasking that occurs with age or neurological conditions¹⁴). Two secondary tasks that can create internal interference and have previously been shown to influence gait^{8, 10}) were chosen for dual-task TUG trials: VF and MCT tasks. To confirm the gait changes captured by the iTUG score, we analyzed movement using a wearable sensor system to calculate time, step count, and gait speed. The wearable sensor system has been used in previous studies to detect gait changes in dual tasking^{15, 16}). We hypothesized that dual-task TUG tasks result in a lower iTUG score (i.e., poorer performance) than single-task TUG (TUG_S).

PARTICIPANTS AND METHODS

Twenty participants volunteered to participate after signing a written informed consent form approved by the Institutional Review Board of West Coast University (IRB No. IORG0010033).

Inclusion criteria were age between 21–64 years and the ability to walk independently with or without assistive devices and understand English instructions. Exclusion criteria were unstable musculoskeletal, neurological conditions, cognitive, vestibular dysfunction, peripheral neuropathy, or any balance instabilities.

All participants underwent the following balance, mobility, and cognition assessments: (1) The Activity-Specific Balance Confidence (ABC) questionnaire is a self-administered questionnaire that allows the individual to rate their perceived confidence to complete 16 activities¹⁷; (2) The Berg Balance Scale (BBS) measures performance on a series of functional tasks¹⁷; and (3) The Montreal Cognitive Assessment (MoCA) assesses cognitive function¹⁸. The assessment protocol took approximately 20 minutes to complete and was used to confirm the inclusion and exclusion criteria. The absence of unstable musculoskeletal, neurological, vestibular dysfunctions, or peripheral neuropathy was confirmed by a written response from each participant before data collection. For cognitive and balance function, we excluded anyone who scored <67 in ABC, \leq 40 in BBS, or \leq 23 in MoCA^{17, 18}. Only one participant was excluded due to a history of a recent concussion.

Following these assessments, participants were instructed to complete the TUG task by getting up from an armless chair (back height: 80 cm, seat height: 39.3 cm, width: 45.7 cm, length: 50.8 cm), walking for three meters, turning around a cone, walking back, and turning before sitting on the same chair. They were instructed to complete the task at a comfortable speed safely. The participants were asked to complete one trial each for the following conditions in a randomized order:

1. TUG_S: single-task TUG

2. TUG + VF task (TUG_{VF}): The TUG was completed while listing words that begin with the letter "R". The participants were instructed not to list pronouns (names, cities, etc.) or variations of words (e.g., rove, roving, rover).

3. TUG + MCT task (TUG_{MCT}): The TUG was completed while participants counted backward by three from a randomly selected two-digit number. All numbers were randomly generated for each participant before the study.

When performing secondary tasks, participants were told to focus on the TUG and secondary tasks equally. In the case of cognitive-motor interference (i.e., interference between secondary tasks "VF or MCT" and TUG), they were instructed to focus on safely moving (i.e., completing the TUG task). Accuracy (%) in VF and MCT tasks was calculated during post-processing using a voice recorder (Lenovo B613 Digital Voice Recorder, Beijing, China) as:

$$Accuracy = \frac{Number of correct responses}{Total responses} \times 100$$

A manual stopwatch (Champion Sports, Marlboro, NJ, USA) was used to capture the time taken to complete the TUG. We used the stopwatch because it is a well-accepted conventional measurement tool that is used commonly by clinicians and has good validity and reliability⁴). A free smartphone application (Hacaro iTUG, Digital Standard Co., Ltd., Osaka, Japan)¹³) was used to capture the total TUG time and iTUG score using an iPhone 6s or iPhone 6 Plus (Apple, Cupertino, CA, USA) that was fixed vertically at the waist level and secured using a belt (Fig. 1). The smartphone application uses inertial gyroscopes and accelerometers to record angular velocity and acceleration, respectively, in three axial directions. The application uses an algorithm to record the raw data at 100 Hz to estimate the iTUG score, which has high test-retest reliability¹³). It also gives the times for each TUG sub-component—sit-to-stand, walk, turn, and stand-to-sit—which were not included in this study. We elected to use this application because the iTUG score provides a more comprehensive gait assessment than the time metric alone. Higher iTUG scores (≥100) reflect good motor performance. A score of 50 reflects mild disability and corresponds to iTUG time of ~13.5 sec, and 95% CE volume of ~70 m³/sec⁶, and a score of ≤0 indicates the inability to



Fig. 1. (A) Locations of the belt-secured smartphone and lumbar sensor used during the study protocol. (B) The smartphone application provides voice and written instructions during the assessment. It operated automatically, but it can also be operated manually. At the end of the trial, the screen shows the iTUG score, total TUG time, and subcomponents' time. (C) The filtered signal of the lumbar pitch angular velocity was measured while a 40 year-old female participant completed the single-task TUG test. Picture (C) shows how the MATLAB algorithm calculated the *start* and *end* times of the TUG based on the first +10°/sec and last -10°/ sec in the pitch angular velocity obtained from the lumbar sensor, respectively^{15, 21}).

walk¹³). Finally, a score between 50 and 100 would indicate a shorter iTUG time (<13.5 sec) and a higher 3D acceleration ellipsoid (approximately between 70–333 m³/sec⁶)¹³). Therefore, we interpreted a lower iTUG score to reflect poorer motor performance (i.e., gait change) than a higher score. The iTUG score calculation is based on the smartphone time and the 95% CE volume estimated from the 3D acceleration data using the formula¹³):

$\frac{(95\% CE volume)^{0.8}}{1.9-1.9 \times (\text{time})+60}$

A Trigno wearable sensor consisting of a tri-axial accelerometer and tri-axial gyroscope was placed on the participants' lumbar spine $(L2-L4 \text{ level})^{19, 20}$. The sensor was wrapped using soft self-adherent tape, and the belt was placed carefully around it to provide more security for the sensor. The *start* and *end* of the TUG test calculated by the wearable sensor were based on an algorithm that was previously validated (Fig. 1)^{15, 21}). A SONY Cyber-Shot DSC-W800 digital camera (Tokyo, Japan) was used to capture the step counts in each trial, and that data were analyzed during post-processing. The dependent variables were as follow:

(1) Total TUG time (sec): this variable is the standard measure for the TUG task⁴); it was simultaneously measured by the stopwatch, the smartphone app, and the wearable sensor. Once the participants heard the "go" verbal cue given by the smartphone application, they started the trial, and the investigator started the stopwatch timing simultaneously. The stopwatch time ended once the back of the participants touched the back of the chair⁴). The smartphone time is programmed to start after giving the "go" command stop once the user sat down on the chair¹³). We synchronized the time measured by the wearable sensor and the stopwatch using a previously published method²²).

(2) Step count (step): this variable was defined as the number of steps taken to complete the TUG test and selected due to its sensitivity to dual-tasking⁸⁾.

(3) Gait speed (m/sec): this variable was defined as the average gait speed during the walking tasks and measured using the wearable sensor with embedded IMU; it is sensitive to dual-tasking⁵).

(4) iTUG score: this variable was calculated by the smartphone application.

(5) DTC of the TUG time, step count, gait speed, and iTUG score (%): this variable reflects the change in motor performance that occurs under dual-tasking conditions, with the lower score reflecting a poorer performance⁸⁾.

The higher scores in TUG time and step count reflects a poorer performance; thus, the DTC for these four variables was calculated as⁸):

$$DTC = -\frac{[(Dual task - Single Task)]}{(single Task)} \times 100$$

Lower scores for gait speed and iTUG score reflect a poorer performance; thus, the DTC for these two variables was calculated as⁸):

$$DTC = \frac{[(Dual task - Single Task)]}{(single Task)} \times 100$$

Prior to recruitment, we first performed a sample size calculation using G*Power software (University Kiel, Germany)²³), and identified that twenty participants would be required to detect the power of 0.8, at an alpha level of 0.05, and an effect size of 0.3^{8}). After data collection and analyses, we first conducted Shapiro-Wilk tests to assess if data were normally distributed for all dependent measures and independently for the three conditions. However, the data were not normally distributed for most variables, and thus, we chose to perform non-parametric tests. We used Friedman's analyses of variance to investigate differences across the three conditions (TUG_S, TUG_{VF}, TUG_{MCT}) for TUG time, step count, gait speed, and iTUG score. If significant results were detected, Wilcoxon signed-rank tests with Bonferroni correction were used to assess differences between the three paired comparisons (p-value set at 0.05 divided by the number of measures tested, i.e., 0.05/3=0.017). We used Wilcoxon signed-rank tests to detect the difference between the DTCs and the accuracy rate between VF and MCT tasks. Effect sizes (ES) were calculated using Rosenthal's equation r=z score/ $\sqrt{N^{24}}$, where N is the sample size and z is calculated via Wilcoxon signed-rank tests. The significance level was set at (p<0.05). All statistical analyses were performed using IBM SPSS Statistics 26 (Armonk, NY, USA).

RESULTS

Participant demographics and clinical characteristics are detailed in Table 1. The mean and standard deviation of the age of the sample was 38.3 ± 12.5 years. The participants' scores in BBS, ABC, and MoCA reflected their normal balance abilities and cognitive function, and none of the participants have reported any unstable conditions. Eighteen individuals (90%) were English-native speakers, 50% had a graduate degree, and 40% were enrolled in a graduate program at the time of data collection.

Descriptive data across conditions are represented in Table 2. The total TUG time measured with a stopwatch differed significantly across conditions ($X^2_F(2)=25.2$, p<0.001). Relative to TUG_S, all participants took a longer time to complete the TUG_{VF} (T=208.50, z=-3.86, p<0.001) and TUG_{MCT} (T=207.00, z=-3.8, p<0.001) tasks. However, there was no difference in TUG times measured by the stopwatch between the TUG_{VF} and TUG_{MCT} conditions. Similarly, wearable sensors-measured TUG times differed significantly across conditions ($X^2_F(2)=11.1$, p=0.004). Participants took longer to complete the TUG_{VF} (T=108.00, z=-2.91, p=0.004) and TUG_{MCT} (T=168.0, z=-2.9, p=0.003) compared to the TUG_S but no significant difference

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Characteristics	Mean	SD	Range		
Age (years)	38.3	12.5	25.0-62.0		
BMI (kg/m ²)	27.3	5.9	21.8-45.2		
MoCA score (0-30)	28.7	1.1	27.0-30.0		
BBS score (0-56)	56.0	0.0	48.0-56.0		
ABC score (0–100)	98.3	1.8	93.1-100.0		
Language fluency		_	_		
English-native (%)	90%				
Non-English native (%)	10%				
Educational level		_	_		
Undergraduate (%)	50%				
Graduate (%)	50%				

Table 1. Demographic and scores on assessment measures

BMI: Body Mass Index; BBS: Berg Balance Scale; ABC: Activityspecific Balance Confidence scale; MoCA: The Montreal Cognitive Assessment. was found between TUG_{VF} and TUG_{MCT} . Finally, TUG times measured with smartphone application were not statistically different across conditions ($X_F^2(2)=4.9$, p=0.08).

Step counts significantly differed across conditions ($X_F^2(2)=25.1$, p<0.001). Participants took more steps to complete the TUG_{VF} (T=136.00, z=-3.6, p<0.001) and TUG_{MCT} (T=120.00, z=-3.6, p<0.001) tasks compared to the TUG_S. No difference was found between TUG_{VF} relative to the TUG_{MCT} (T=36.00, z=-0.9, p=0.03).

Gait speed also differed significantly across conditions ($X^2_F(2)=3.9$, p=0.01). Participants walked slower during the TUG_{VF} (*T*=31.00, *z*=-2.76, p=0.006) and TUG_{MCT} (*T*=33.0, *z*=-2.7, p=0.004) tasks compared to the TUG_S. No statistical difference was found in gait speeds between the TUG_{VF} and TUG_{MCT} tasks (*T*=103.0, *z*=-0.07, p=0.9).

Participants showed a significant decrease in the iTUG score across conditions ($X_F^2(2)=14.7$, p<0.001). They had significantly lower scores on the TUG_{VF} (*T*=9.0, *z*=-3.58, p<0.001) and TUG_{MCT} (*T*=40.5, *z*=-2.4, p=0.01) tasks compared to the TUG_S. Although a trend suggesting that the VF task created more motor disturbance than the MCT task, there was no significant difference between the TUG_{VF} and TUG_{MCT} tasks (*T*=52.0, *z*=-1.9, p=0.04).

There was no significant difference in DTC of all six variables when completing the VF versus the MCT tasks, and neither in the accuracy rates (all p>0.05).

DISCUSSION

Examining motor patterns is a crucial component of physical therapy assessments. Detecting and identifying gait changes can shape the targeted interventions and improve patient independence, especially in those at high risk of postural instabilities. Detailed gait assessments are not feasible in all clinics due to the high cost of 3D motion analysis systems or lack of expertise. Further, the move to telehealth opened up additional opportunities that clinicians can practice, and smartphone

Table 2.	Medians	(interc	uartile	range)	for	the d	ependent	t variable	s are	presented
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Variable			Freidman ANOVA p- value (across 3 conditions)	Wilcoxon Test (p-value, effect size)			
	TUG _S	TUG _{VF}	TUG _{MCT}		TUG _S vs. TUG _{VF}	TUG _S vs. TUG _{MCT}	TUG _{VF} vs. TUG _{MCT}
Stopwatch total TUG	6.8	8.9	8.1	<0.001	(<0.001 , 0.8)	(<0.001 , 0.8)	(0.05, 0.4)
time (sec)	(6.0 to 8.3)	(7.2 to 10.2)	(6.4 to 10.0)				
Wearable sensor total	7.2	7.8	7.8	0.004	(0.004 , 0.6)	(0.003 , 0.6)	(0.2, 0.2)
TUG time (sec)	(6.3 to 8.2)	(7.3 to 10.1)	(6.9 to 9.9)				
Smartphone total TUG	8.5	9.3	9.2	0.08	(0.01, 0.5)	(0.06, 0.4)	(0.2, 0.2)
time (sec)	(7.4 to 10.1)	(8.6 to 10.4)	(7.7 to 11.0)				
Step count (step)	11.0	13.0	12.5	<0.001	(<0.001 , 0.7)	(<0.001 , 0.7)	(0.3, 0.1)
	(10.0 to 12.8)	(12.0 to 14.0)	(11.2 to 14.5)				
Gait speed (m/sec)	2.1	1.8	1.8	0.01	(0.006 , 0.6)	(0.007 , 0.6)	(0.9, 0.01)
	(1.6 to 3.0)	(1.2 to 2.6)	(1.3 to 2.5)				
iTUG score	96.7	78.3	81.9	<0.001	(<0.001 , 0.8)	(0.01 , 0.5)	(0.04, 0.4)
	(80.9 to 127.4)	(64.2 to 108.8)	(72.1 to 123.3)				
DTC of stopwatch total		-22.7	-12.5				(0.07, 0.3)
TUG time (%)		(-26.3 to -10.2)	(-21.9 to - 6.0)				,
DTC of wearable sensor		-17.5	-8.8				(0.1, 0.3)
total TUG time (%)		(-21.4 to -5.8)	(-17.5 to -0.12)				
DTC of smartphone total		-13.2	-10.7				(0.1, 0.2)
TUG time (%)		(-25.3 to 0.9)	(-22.5 to 3.4)				
DTC of step count (%)		-19.1	-16.7				(0.3, 0.2)
• • • • •		(-22.0 to -6.4)	(-21.0 to -2.2)				
DTC of gait speed (%)		-14.1	-12.7				(0.9, 0.008)
		(-27.2 to -1.6)	(-24.9 to 0.06)				
DTC of iTUG score (%)		-14.1	-12.5				(0.05, 0.4)
		(-30.3 to -10.5)	(-26.2 to 3.2)				
Accuracy rate (%)		100.0	100.0				(0.3, 0.1)
• • • •		(91.7 to 100.0)	(100.0 to 100.0)				

Significant values are displayed in **bold** (p<0.05 for Friedman ANOVA and p=0.05/3=0.017 for Wilcoxon test. DTC: dual-tasking cost; TUG_S: single-task TUG; TUG_{VF}: TUG with verbal fluency task; TUG_{MCT}: TUG with mental calculation task.

applications can be used as objective tools due to their high accessibility^{3, 25)}. However, they need to be tested in different conditions that mimic day-to-day scenarios before being implemented in clinical practice. The present study examined the ability of a smartphone application to detect gait changes in attention-demanding conditions. Although our results indicate that the iTUG score can discriminate between gait changes in the VF and MCT tasks compared to single-task iTUG, there are some challenges regarding its use.

While the iTUG score showed potential to identify gait changes during the TUG_{VF} and TUG_{MCT} tasks (compared to the TUG_s), the smartphone application has two issues that need to be addressed. First, unlike the time obtained by the wearable sensor, the total time calculated by the application was typically higher relative to the stopwatch time, especially in TUG₅. The smartphone application estimated the start and end times of the TUG as 0° /sec and -50° /sec in the pitch angular velocity signal, respectively¹³), while the wearable sensor used in this work and another studies^{15, 21}) defined the *start* and *end* of the TUG as the first 10° /sec and last -10° /sec in the pitch angular velocity signal, respectively, obtained from the lumbar sensor. We noticed that the smartphone application was limited in estimating the end time. Several trials had to be repeated because the application did not stop when some participants sat down to complete the TUG task. In the TUGs, the participants walked faster and sat down quicker than in dual-task runs. Thus, it is possible that the application failed to detect the accurate end time of the actual trial during the TUGs more than the dual-tasking TUG. Furthermore, if the application has a fixed error when estimating time, the error effect would be more prominent on a shorter test (e.g., the TUG_S) relative to a longer one (e.g., the dual-tasking TUG). In previous research, the iTUG score successfully captured gait variation after a shunt surgery or tap test that required removal of cerebrospinal fluid in individuals with idiopathic normal-pressure hydrocephalus¹³). It should be noted that they included a patient population with more significant gait variability compared to the healthy adult participants in our study. Second, the smartphone time did not differ across conditions in our study, unlike other dependent variables, including the iTUG score. Since the iTUG score depends on smartphone time and the 3D acceleration ellipsoid, we speculate that the latter was a more sensitive measure to dual-tasking changes than the imprecise smartphone time. In line with this result, it was reported that the smartphone time was a reliable measure for gait changes assessment only at ≥ 13.5 sec; Whereas emphasis should be directed toward evaluating the 3D acceleration ellipsoid at <13.5 sec¹³⁾. Hence, we expect that the smartphone time was not a reliable measure in this sample of healthy adults as only 8.3% (5/60) of the data was >13.5 sec.

To confirm the gait changes captured by the iTUG score, we analyzed spatiotemporal measurements using the wearable sensor, which can detect changes in movement under dual-tasking conditions¹⁵⁾. We found significant difference in gait speed and step count, which align with the change in iTUG score, in dual-tasking conditions relative to single-task condition. To maintain stability and cope with dual-task TUG objectives, individuals walked slower and took more steps than TUG_s. Our results are in line with previous findings in this population that demonstrated negative impacts of dual-tasking on gait parameters such as time, gait speed, stride length, and step-time variability^{5, 8–10)}. A trend emerged in our data suggesting that the VF task can be more challenging than the MCT task; however, cognitive-motor interference did not differ significantly between VF and MCT tasks. This may occur due to the small sample size and is in line with Patel et al.'s¹⁰ findings on healthy adults. In contrast, other studies showed that the VF task could create a greater cognitive-motor interference than the MCT task^{8, 16}. The discrepancy in results could also emerge due to the unique characteristics of the recruited samples. For instance, only 10% of our sample were non-English native speakers compared to 50% of the sample used in other work⁸, which was cited as a potential factor for decreased performance in the VF task. Additionally, 50% of our sample had a graduate degree, and 40% were enrolled in a graduate program at the time of the data collection. Hence, improvement in the MCT and VF accuracy metric is likely due to high educational levels in our sample²⁶.

The findings must be considered within the context of the study's limitations. First, we assessed a small sample of healthy adults at a low risk of fall, limiting the generalizability of our results to other populations at a higher fall risk. We controlled for factors that can increase the variability of TUG performance such as cognitive, balance, or neuromuscular problems. However, age, education, and native language may influence the findings of this pilot study^{8, 15, 26)}. Thus, an additional study with a larger cohort, controlling for those variables, is necessary to confirm the results. Second, the smartphone application was limited in detecting trunk movements in several trials (8/60) when the participants sat down and moved after contacting the chair's back. When this occurred, we repeated the trials and re-instructed the participant to sit still so the time count would stop at task completion. Furthermore, two different iPhones were used for data collection, which could introduce bias if the application developers did not compensate for the different noise levels in raw sensors across iPhone models²⁷⁾. However, we doubt that this would be substantial, if any, as both models were of iPhone 6 series. Finally, we used two complex secondary tasks that create greater motor-cognitive interference than other secondary reaction time tasks^{8, 9)}. Whether the smartphone application will detect gait changes with other secondary tasks remains unclear and should be explored in future studies.

In summary, the smartphone application is a practical tool that can assess motor behavior in dual-tasking conditions. Still, some issues need to be considered, such as the unreliable smartphone time at <13.5 sec. The iTUG score can detect motor decrements in attentional demanding conditions. We found that the cost-effective traditional measurement of step count and stopwatch time commonly used in rehabilitation settings can also differentiate motor patterns under the dual-tasking conditions tested in our paradigm. Future work is warranted to improve this application's quality and make it available for other smartphone operating systems such as Android, which are cheaper than the iPhone.

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No potential conflict of interest was reported by the authors.

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