Investigating the AX6 inertial-based wearable for instrumented physical capability assessment of young adults in a low-resource setting

Dylan Powell[a], Mina Nouredanesh[b], Samuel Stuart[c] Alan Godfrey[a*]

[a]*Department of Computer and Information Sciences, Northumbria University, Newcastle upon Tyne, NE1 8ST, UK*
[b]*Department of Mechanical and Mechatronics Engineering, University of Waterloo, 200, University Ave. W, Waterloo, Canada*
[c]*Department of Sport, Exercise and Rehabilitation, Northumbria University, Newcastle upon Tyne, NE1 8ST, UK*

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Abstract
Instrumented balance and gait test are an important component of physical capability assessment in clinical examinations. This study provides insight to a new generation Open Movement inertial-based wearable (AX6, Axivity, UK) compared to a previously validated reference (AX3). The AX6 was assessed for its ability to quantify a battery of tasks that represent a composite physical capability assessment. Participants wore both wearables on the lower back (5th lumbar vertebrae) continuously throughout the testing period. No significant differences ($p<0.05$) were found between the AX6 and reference wearable (AX3) for time taken to complete the following tasks: four-meter walk ($p=0.18$), sit to stand ($p=0.05$), and timed up and go ($p=0.55$). Bland-Altman analysis plots suggest good to excellent agreement between the AX6 and reference (AX3) device with low discrepancy in mean differences and narrow limits of agreement. Significant differences were found between the AX6 and manual recorded times in the four-meter walk test and 2-minute walk test, and no significant differences in sit-to-stand and timed-up-and- go were observed. Temporal data for both wearables were compared with no differences in step time, stride time, swing time and stance time. Differences were observed for spatial digital biomarker/characteristic (step length). This study shows the AX6 to be a reliable device for objectively quantifying data from physical capability tasks. These findings also reinforce the advantages of using open source, instrumented testing and methods for physical capability and disease monitoring.

* Corresponding author. Tel.: +00-44-191-3642; e-mail: alan.godfrey@northumbria.ac.uk

1. Introduction

Physical capability/functioning tasks aim to examine balance and gait under observation whereby optimal function of both will demonstrate adequate performance in underlying neural systems (Alberts et al., 2015; A. Godfrey, Lara, Del Din, et al., 2015; Stuart, Hickey, Morris, O'Donovan, & Godfrey, 2017). Thus, balance and gait tests are an important component of clinical and physical capability assessments (Alberts et al., 2015; A. Godfrey, Lara, Del Din, et al., 2015; Paul McCrory et al., 2017; Stuart et al., 2017). They are routinely investigated in a range of conditions such as Parkinson's disease (Mancini et al., 2012; Morris et al., 2017) and mild traumatic brain injury (mTBI) (Fino et al., 2018; Howell, Osternig, & Chou, 2015) where the latter may arise in sporting contexts due to sports related concussion (SRC) (Marshall & Spencer, 2001; P. McCrory et al., 2009; Paul McCrory, Meeuwisse, Kutcher, Jordan, & Gardner, 2013; Tator et al., 2019; Trahan, Ross, & Trahan, 2001). Incidence of mTBI arising from SRC is growing (Theadom et al., 2020). Current routine approaches to diagnose athletes/patients occur during infrequent, snap-shot assessments. Typically, the latter is conducted in low-resource settings (e.g., training ground, sports club) using subjective observations with paper-based tools to score balance and gait deficits. There is a need to assess (objective) digital approaches in the same settings to augment and potentially improve SRC diagnosis.

Wearable technologies such as inertial measurement units (IMU) are becoming increasingly popular for instrumentation of tasks, due to attachment at any anatomical location without any burden and provision of raw (sample level) data. The ability to apply novel algorithms to propose new digital approaches to traditional tests such as the instrumented timed-up-and-go (iTUG) is of interest. For example, iTUG (Salarian et al., 2010), used several anatomically placed IMUs with a central data logger (Physilog, BioAGM, CH) (Aminian, Najafi, Büla, Leyvraz, & Robert, 2002) to provide objective TUG times as well segmentation of the TUG into various components (sit-to-stand, walk, turn, etc). Accordingly, iTUG provides detailed spatial and temporal data for digital biomarkers related to balance, turning and gait (Salarian et al., 2010). Although assessment with multiple IMUs provides an abundance of clinical data, it yields different limitations such as longer data download and processing complexity. Alternatively, use of a single low-cost IMU-based wearable may facilitate more clinically translatable and insightful approaches (A. Godfrey, Barry, Mathers, & Rochester, 2014). For example, a single tri-axial accelerometer-based wearable (AX3, Axivity, UK) has shown promise for use in low-resource settings to yield pragmatic balance and gait data across a holistic battery assessment of physical capability (Del Din, Godfrey, & Rochester, 2016; A. Godfrey, Del Din, Barry, Mathers, & Rochester, 2014; A. Godfrey, Lara, Del Din, et al., 2015; Kongsvold, 2016; Sliepen & Rosenbaum, 2016). The AX3 has been of particular interest for use in healthcare as it is developed under Open Movement (OM[1]), which is of growing interest as clarification and transparency on how wearables are created for generating digital biomarkers is of increased importance (A. Godfrey et al., 2020; Alan Godfrey et al., 2021; Goldsack et al., 2020). OM fosters open-source code for firmware and software made available under a BSD 2-clause license[2], while the hardware (e.g., PCB designs and schematics), enclosure designs and documentation are made available under a Creative Commons 3.0 BY Attribution License[3], to reduce research project costs and

[1] https://opendatahandbook.org/glossary/en/terms/open-movement
[2] https://opensource.org/licenses/BSD-2-Clause
[3] https://github.com/digitalinteraction/openmovement

overcome black-box development (A. Godfrey et al., 2018). Investigation of these more transparently developed wearables will be key to see their pragmatic use in healthcare applications.

This study aims to investigate the new IMU-based wearable developed under OM, the AX6 (Axivity, UK) as a pragmatic tool to instrument physical capability of younger adults in a low-resource setting. To do so we investigate its robustness to quantify physical capability outcomes in comparison to another OM wearable (AX3). The AX3 was chosen as it is (i) validated in a range of physical capability/functioning studies with use of previous algorithms (to be implemented here) (Del Din et al., 2016; A. Godfrey, Del Din, et al., 2014; A. Godfrey, Del Din, Barry, Mathers, & Rochester, 2015; A. Godfrey, Lara, Munro, et al., 2015) and (ii) the most suitable comparative reference where instrumented walkways or 3D motion analysis would not be suitable (Del Din et al., 2016). The aim here is to determine the suitability of the AX6 accelerometer-based data as an equally useful tool for physical capability testing in generic, low-resource settings for use during SRC diagnosis. Additionally, we broadly investigate use of the AX6 gyroscope to augment accelerometer data during physical capability testing. It is hypothesized that the AX6 accelerometer data will provide robust outcomes and additional sensing capabilities (gyroscope) would provide additional objective digital biomarkers (compared to the AX3) within SRC.

2. Materials and Methods

2.1. Participant recruitment

University students were invited to take part in this study. Inclusion criteria included ≥18 years, English as a first language and with no impairment which would prohibit them from safely performing functional tasks. Those interested were then given a participant information sheet which detailed the study. Ethical consent for the project was granted by the Northumbria University ethical committee (Reference: 3672). All participants gave informed written consent prior to testing, which took place at Northumbria University Sport Central, Newcastle-upon-Tyne.

2.2. Equipment

Supervised assessment was conducted using the low-cost/accessible AX6 (Axivity[4]. 2.3×3.3×0.8 cm, 11g). The AX6 has configurable tri-axial accelerometer (±2-16g) and tri-axial gyroscope (125-2000 degrees per second, dps) sensor (Bosch, BMI160) with variable sampling capabilities (e.g., 50 or 100Hz), set via proprietary software (OmGUI[5]). Here, AX6 was programmed to ±8g, 250dps and 100Hz. The AX6 and reference device were placed as close as possible to the 5th lumbar vertebrae (L5) with double sided tape to quantify all tasks. The AX6 was placed to the right of L5, while the reference was placed to the left, Fig. 1. L5 was chosen based on algorithms used (section 2.5). Participants wore the AX6 and reference continuously. Manual timed recordings were taken for completeness as this method is often used in low-resource settings to establish validity. Here, we also use manual recordings to provide insight to those investigating wearables for functional testing, highlighting where discrepancies may arise between methods. Upon completion of recording, participants were verbally asked if they found the devices comfortable to wear during all assessments. The AX6 and AX3 were time synchronized from the same research computer.

2.3. Reference standards

The previously validated accelerometer only sensor-based (ADXL345, Analog Devices) AX3 (2.3×3.3×0.8 cm, 11g) wearable was used (located beside the AX6 on L5, Fig. 1). The AX3 was programmed similar to the AX6 (±8g, 100Hz) via proprietary software. The AX3 was previously investigated and validated for use during physical functional assessment in laboratory (A. Godfrey, Del Din, et al., 2015) and low-resource settings (A. Godfrey, Lara, Munro, et al., 2015).In brief, the referenced studies studied the AX3 in comparison to video, instrumented walkway and direct observation to assess its suitability for physical functioning assessment. For example, the laboratory study used video data to segment periods of walking to compare young adult (28.6years) AX3 derived gait characteristics to a GaitRite system with results showing good to excellent agreement between both.

Observational pen-and-paper timings with a stopwatch were taken by a trained researcher. Manual timings were taken for completeness as this method is often used in low-resource settings to establish validity. Upon completion of recording, participants were verbally asked if they found the devices comfortable to wear during all tasks. The AX6 and AX3 were time synchronized from the same computer.

[4] https://axivity.com

[5] https://github.com/digitalinteraction/openmovement/wiki/AX3-GUI

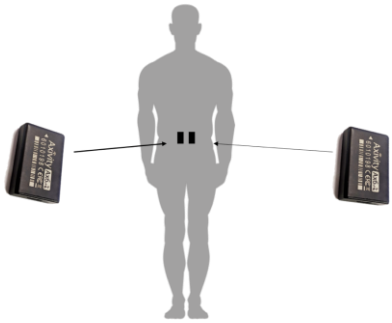

Fig. 1 attachment of the AX6 (left) and reference device (AX3, right) on the 5th lumbar vertebrae (L5).

2.4. Experimental protocol

Here we adopted a similar protocol as previously presented (A. Godfrey, Lara, Del Din, et al., 2015). Each task (except #4 and #5) had a practice followed by a repeated performance as follows:

- Task #1 locomotion, 4m gait speed test (×2 i.e., performed twice): After a practice, participants walked at their usual speed/pace between two markers 4m apart. AX6 (and AX3) timing began upon the first step taken. Recording ended after the participant completed the walk (manual, by stopwatch) or last purposeful footfall (as detected by wearables). The latter was determined from the vertical acceleration (a_V) exceeding a predetermined threshold. Time to complete the 4m walk was converted into a meters-per-second metric. Algorithm A, Table 1.
- Task #2 lower limb strength, repeated sit-to-stand-to-sit transitions (×2): Participants went from a sitting posture to standing to sitting five times as quickly as possible, with arms folded across their chest. After a practice, participants were instructed to have full extension in their knees and not to touch the back of the chair during each repetition. Algorithm B, Table 1.
- Task #3 lower-limb-strength and locomotion, TUG (×3): After a practice, participants stood up from a chair (height: 40–50cm), walked 2m at a normal pace, around a cone, back to the chair, turned and sat. TUG time was recorded manually as the time from initiation of chair rise and ended when the participants back touched the backrest of the chair. Algorithm B, Table 1.
- Task #4 endurance, total distance during a 2min walk: Participants walked continuously and as fast as they could without running. The route consisted of walking back and forth around cones (10m apart). Wearable-based total distance walked was calculated by summing total step length. Algorithm A and C, Table 1. For observational/manual records, the number of laps were counted.
- Task #5 standing balance, postural control: Five tests were performed (50s each). During tests participants did not wear shoes, placed hands on their hips and focusing on a wall-mounted fixed point at a distance of 1m. Algorithms D, E and F, Table 1. Tests consisted of:
    - (1a) standing on a flat hard surface, their feet together, eyes open;
    - (1b) standing on a flat hard surface, their feet together, eyes closed;
    - (1c) standing on a foam surface (1.5m x 1m x 0.04m), feet together, eyes open;
    - (2a) standing on a foam surface, feet together, eyes closed;
    - (2b) standing on a flat hard surface, feet in a tandem stance (i.e. one foot behind the other), eyes open.

For repeated timed tasks the average was taken, normal practice for physical capability testing under observation (all timed data is presented for clarity). To aid data segmentation for all tasks, participants were asked to hop/jump three times to create acceleration peaks in the tri-axial data.

2.5. Algorithms

Raw IMU data were manually segmented via MATLAB® (R2020a, MathWorks Inc., Massachusetts, USA) *ginput* function, made readily possible by the identification of hop/jump data peaks examined from visual observations. Asking participants to hop/jump before each task generated acceleration peaks, not representative of data acquired during tasks.

Data pertaining to Tasks 1 to 5 were analyzed with previously validated instrumented physical capability algorithms (A. Godfrey, Lara, Munro, et al., 2015), Table 1. For example, raw vertical acceleration was filtered by integrating and then differentiating using a Gaussian continuous wavelet transform (CWT) to examine signal local minima, which corresponded to initial contact (IC) times during gait. Subsequently, final contact (FC) events were identified as the signal maxima obtained from a further CWT (McCamley, Donati, Grimpampi, & Mazzà, 2012). Additional IC and FC details can be found elsewhere (A. Godfrey, Del Din, et al., 2015). Algorithm G (Table 1) was used to deriving temporal gait outcomes.

Once IC and FC were correctly estimated, the inverted pendulum model was used to calculate step length and therefore total distance covered (W. Zijlstra & Hof, 1997; Wiebren Zijlstra & Hof, 2003). In brief, use of the same inertial data located on L5 can track the center of mass (COM) trajectory during walking to predict amplitude and timing of pelvic displacement (Algorithm H, Table 1).

Furthermore, the discrete wavelet transform (DWT) with a 5th scale approximation (with a Meyer wavelet) was used to examine the signal vector magnitude of combined tri-axial acceleration data during postural transition tasks (Bidargaddi et al., 2007). The full details of algorithms and processes are detailed elsewhere (A. Godfrey, Lara, Munro, et al., 2015). Additionally, we examined the ability of the AX6 (gyroscope) to correctly identify all turns during TUG and endurance tasks, by examining the peak angular velocity along the appropriate sensing axis Specifically, turning events (Algorithm I, Table 1) were detected using the horizontal rate of the AX6, >15°/ sec represented a turn, with the start and end of turns set to point where rate dropped below 5°/sec, with a minimum of 45° trunk rotation around the vertical plane and duration of 0.5-10 secs required for classification (El-Gohary et al., 2013). We compared AX6 detected turns to manual counts.

Table 1 *Algorithms and features for physical capability quantification*

Algorithms	Description and used in tasks	Representation
A	Detecting initial contact (IC) and final contact (FC) times from gait cycle *Tasks: 1 and 4*	$W(a,b) = \frac{1}{\sqrt{\lvert a \rvert}} \int_{-\infty}^{\infty} x(t)\psi * \left(\frac{t-b}{a}\right) dt$ The transformed signal is a function of two variables *b* and *a*, which are the translation and scale parameters, respectively. The transforming (wavelet) function ($\psi(t)$) is defined as the 'mother wavelet'
B	Chair rise and sit detection and total time estimations *Tasks: 2 and 3*	$x(t) = \sum_{k=-\infty}^{\infty} \sum_{\ell=-\infty}^{\infty} d(k,\ell) 2^{-k/2} \psi(2^{-k}t - \ell)$ DWT owes its functionality to the fast pyramid algorithm, as developed by Mallat and Meyer (Bruce, Donoho, & Gao, 1996; Semmlow & Griffel, 2014). The pyramid algorithm has both forward and backward (inverse) algorithms to compute the wavelet transform. The backward algorithm reconstructs the original signal from the component wavelets (A. Godfrey, Conway, Meagher, & ÓLaighin, 2008).
C	Step length (using IC/FC detection) *Task: 4*	Step length=$2\sqrt{2lh - h^2}$ Changes in height (*h*) can be calculated (double integration of a_v) in which *l* refers to the pendulum length (i.e. height of the inertial wearable from the ground to place of attachment)
D	Root mean square, RMS (m/s^2)	Root mean square of tri-axial signals $RMS = \sqrt{\frac{1}{n}(a^2{}_{M1} + \ldots\ldots a^2{}_{Mn})}$
E	Jerk (m^2/s^5)	First derivative of acceleration signal $JERK = \frac{1}{2}\int_0^t \left(\frac{da_{PA}}{dt}\right)^2 + \left(\frac{da_{ML}}{dt}\right)^2$
F	Sway (area, mm^2/s^5) *Task: 5 (D, E and F)*	$A = \sqrt{a_x{}^2 + a_y{}^2 + a_z{}^2}$, $\alpha = \cos^{-1}(\frac{a_x}{A})$, $\beta = \cos^{-1}(\frac{a_y}{A})$ $\gamma = \cos^{-1}(\frac{a_z}{A})$, $d_x = D * \cos\alpha$, $d_y = D * \cos\beta$
G	From estimated IC/FC data, where *i* denotes an incremental value within the array *Task: 1 (used in conjunction with algorithm A)*	Step time (i) = IC (i + 1) – IC (i); Stance time (i) = FC (i + 1) – IC (i); Stride time (i) = IC (i + 2) – IC (i); Swing time = Stride time – Stance time.
H	Estimating pelvic displacement (*h*) derives step length and consequently step velocity *Task: 4 (used in conjunction with algorithm A and B)*	Step length = 2(sqrt(2*(Wearable Height) *h–h^2)); Step velocity = Step length / Step time;
I	Turn estimation detection from the vertical axis, after 1.5 Hz cutoff frequency Butterworth filter. *Task: Turning estimation.*	From segments where the maxima of the filtered axis exceed a threshold of 15°/s. The start and end of each turn are set to the point where the filtered axis is < 5°/s.

2.6. Statistical analysis

Data were tested for normality and linearity of distributions by plotting and inspecting histograms and Quintile-Quintile (Q-Q) plots, respectively. Difference between pairs were found to be normally distributed and so Pearson's correlation was used to assess linear correlations. Paired sample t-tests are commonly used to test differences between means and whether two samples are different from each other and used here to test for differences between AX6 and references (AX3 and manual). Bland-Altman plots help compare agreement (mean differences) between e.g., technologies (Giavarina, 2015) and were used to investigate device limits of agreement (LoA) between the AX3 to AX6.. For all analysis, statistical significance was set at $p<0.05$.

3. Results

Twelve participants were recruited (12 male, 20years ± 0.82, 181.69cm ± 6.84, 91.01kg ± 10.59). All participants reported no issues/problems with any wearable, stating they were comfortable to wear during all tasks. For all tasks (except some standing balance variations), participants wore their usual footwear/shoes. In general, there were no significant differences between the AX6 and reference device and most correlations were statistically significant. There were some statistical significant differences between the AX6 and manual recordings, Table 1.

3.1. Locomotion (four-meter walk test)

There was a strong positive correlation between the AX6 and reference device ($r \geq 0.88$) for individual and average walks, Table 2. No significant differences were found for time to complete individual 4-meter walking task 1 and 2 ($p=0.15$ and 0.66) or average time ($p=0.18$). Bland-Altman plot (Fig. 2i) shows low discrepancy in mean differences and narrow LoA between wearables, suggesting good to excellent agreement. AX6 and manual recordings showed no significant differences ($p>0.05$) in trial 1, but significant differences in trial 2 and average times ($p<0.05$).

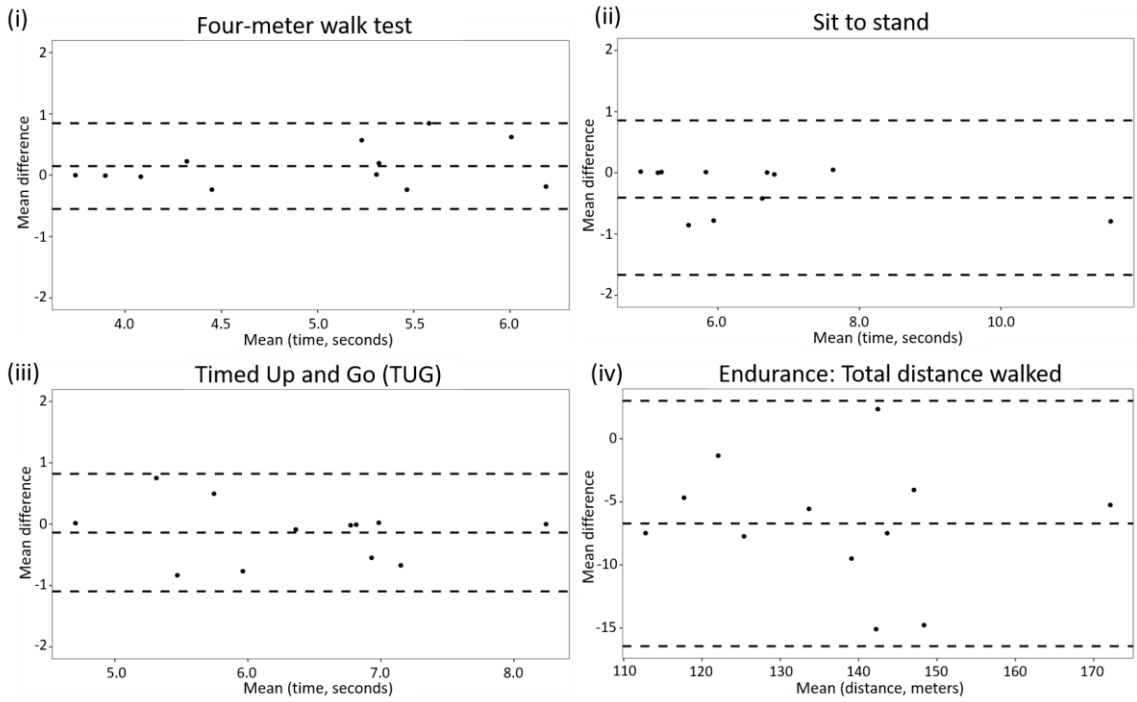

Fig. 2 Bland-Altman plots showing agreement between AX6 and reference device for averaged time in seconds (i) 4m walk test, (ii) sit-to-stand-to-sit transitions, (iii) Timed Up and Go. (iv) Shows total distance (m) from the two-minute walking endurance task

Table 2 *Mean ± SD values in seconds and meters for AX6 to compared to reference measures (*p < 0.05)*

Task- test	Trial #	AX6 Mean ± SD	Reference (AX3) Mean ± SD	Pearsons Correlation *r*	Pearsons Correlation *p*	Paired t-test *p*	Reference (Manual) Mean ± SD	Paired t-test *p*
4-meter walk (s)	1	5.12 ± 1.15	5.35 ± 1.24	0.92	0.00*	0.15	5.78 ± 0.77	0.09
	2	4.66 ± 0.85	4.73 ± 1.08	0.88	0.00*	0.66	5.36 ± 0.68	0.01*
	Average	4.89 ± 0.76	5.04 ± 0.87	0.92	0.00*	0.18	5.57 ± 0.61	0.02*
Sit-to-stand (s)	1	6.40 ± 1.75	6.08 ± 1.35	0.92	0.00*	0.17	6.16 ± 1.63	0.59
	2	7.18 ± 2.04	6.68 ± 2.17	0.94	0.00*	0.05	6.16 ± 1.57	0.02*
	Average	6.79 ± 1.82	6.38± 1.64	0.94	0.00*	0.05	6.16 ± 1.57	0.11
TUG (s)	1	6.82 ± 1.05	6.88 ± 0.94	0.93	0.00*	0.58	6.23 ± 0.74	0.10
	2	6.55 ± 1.01	5.86 ± 1.12	0.17	0.60	0.12	6.24 ± 0.71	0.13
	3	5.73 ± 1.3	5.97 ± 1.02	0.90	0.00*	0.21	6.48 ± 0.71	0.90
	Average	6.44 ± 1.00	6.30 ± 0.92	0.88	0.00*	0.55	6.24 ± 0.73	0.45
	Total turns	72.00 ± 0.00	--	--	--	--	72.00 ± 0.00	1.00
2-minute walk (m)	1	140.57 ± 16.01	133.85 ± 15.42	0.95	0.00*	0.00*	196.67 ± 19.72	0.00*
Turns	All walks	18.67 ± 2.06	--	--	--	--	18.67 ± 2.06	1.00

3.2. Lower limb strength (sit-to-stand)

There was a strong positive correlation ($r \geq 0.92$) and no significant differences between the AX6 and reference device for time taken across both trials and averaged time. Bland-Altman plot (Fig. 2ii) shows good to excellent agreement. There was a significant difference between the AX6 and manual recordings for trial 2 ($p=0.02$) but not for task 1 ($p=0.59$) and average ($p=0.11$).

3.3. Lower limb strength and locomotion (TUG)

Generally, there was a strong correlation ($r=0.88$). There were no significant differences between the AX6 and reference for time taken to complete across individual or averaged trials (Table 2). Bland-Altman (Fig. 2iii) shows good to excellent agreement. No significant differences were observed for averaged times between the AX6 and manual recordings ($p \geq 0.10$). The AX6 correctly identified all turns (72 in total) during the TUG test compared to manual observations, Table 2.

3.4. Endurance (2-minute walking task)

There was a significant ($p<0.01$) positive correlation ($r=0.95$) between AX6 and reference for total distance walked but total distances were significantly different ($p<0.01$). Bland-Altman (Fig. 2iv) shows moderate agreement with no outliers outside the upper or lower LoA. Significant differences were also found between AX6 and manual estimations ($p<0.01$).

3.4.1 Spatial and temporal gait

There were strong correlations between devices for all spatial and temporal characteristics ($r>0.72$). No significant differences were found in step time ($p=0.60$), stride time ($p=0.60$), swing time ($p=0.78$), stance time ($p=0.52$) or step velocity ($p=0.38$). However, step length showed a significant difference ($p<0.01$). Bland-Altman analysis was conducted for each outcome, Fig. 3. For example, stride time (Fig. 3-ii), showed good to excellent agreement with very narrow bias in mean difference and no outliers.

Table 3 *Temporal and spatial gait characteristic estimations from AX6 compared to reference AX3*

Task	Characteristics	AX6	Reference (AX3)	Pearsons correlation		Paired sample t.test
		Mean ± SD	**Mean ± SD**	***r***	***p***	***p***
Endurance (2min walk)	Step time (s)	0.46 ±0.04	0.46 ± 0.04	0.99	0.00*	0.60
	Stride time (s)	0.91 ± 0.08	0.91 ± 0.08	0.99	0.00*	0.60
	Swing time (s)	0.32 ± 0.03	0.32 ± 0.03	0.99	0.00*	0.78
	Stance time (s)	0.59 ± 0.06	0.59 ± 0.05	1.00	0.00*	0.52
	Step length (m)	0.55 ± 0.08	0.52 ± 0.07	0.72	0.01*	0.00*
	Step velocity (ms^{-1})	1.18 ± 0.18	1.14 ± 0.11	0.76	0.00*	0.38

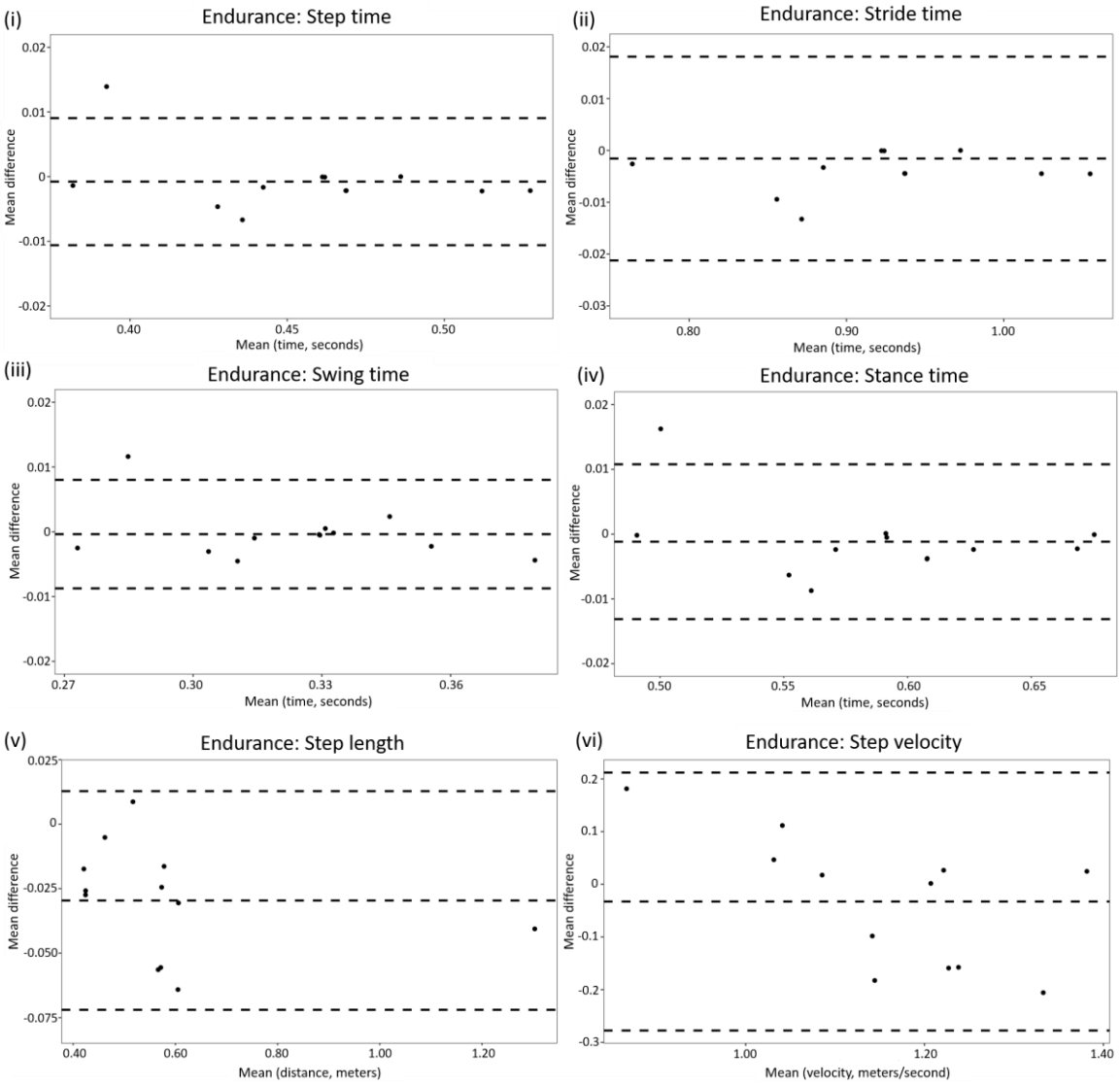

Fig. 3 Bland-Altman plots showing agreement between AX6 and reference device for spatial and temporal gait characteristics/biomarker during the endurance 2- minute walking task (i) step time (s), (ii) stride time (s), (iii) swing time (s), (iv) stance time (s), (v) step length (m) and (vi) step velocity (m/s)

3.5. Standing balance

Table 4 provides RMS, Jerk and Sway values for each of the postural control tasks, 1a to 2b. The increasing difficulty of each task has only a small impact in RMS values. Jerk increases as tasks become more difficult (1a to 2b). Similarly, sway shows large changes in values between tasks. There were strong positive correlations in all tasks between AX6 and reference (AX3) across RMS, Jerk and Sway. There were significant differences ($p<0.05$) in RMS across all tasks between AX6 and reference. Contrastingly there were no significant differences ($p>0.05$) between AX6 and reference for Jerk and Sway (1a to 2b).

Table 4 *Postural control tasks (1a, 1b, 1c, 2a, 2b) for the AX6 and reference (AX3) with RMS, Jerk and Sway outcomes*

Trial	**AX6 RMS ($mm.s^{-2}$)**	**Reference (AX3) RMS ($mm.s^{-2}$)**	**Pearsons correlation**		**Paired t-test**	**AX6 Jerk ($m^2.s^{-5}$)**	**Reference (AX3) Jerk ($m^2.s^{-5}$)**	**Pearsons correlation**		**Paired t-test**	**AX6 Sway ($x10^5\ mm^2s^{-5}$)**	**Reference (AX3) Sway ($x10^5\ mm^2s^{-5}$)**	**Pearsons correlation**		**Paired t-test**
			r	***p***	***p***			***r***	***p***	***p***			***r***	***p***	***p***
1a: Hard surface, feet together, eyes open	0.99 ± 0.01	1.04 ± 0.02	0.49	0.11	0.00*	13.39 ± 12.1	12.98 ± 11.65	0.99	0.00*	0.38	0.92 ± 4.77	0.73 ± 5.20	1.00	0.00*	0.25
1b: Hard surface, feet together, eyes closed	0.99 ± 0.02	1.05 ± 0.02	0.82	0.00*	0.00*	15.02 ± 11.45	14.90 ± 11.61	0.98	0.00*	0.84	59.02 ± 188.50	59.61 ± 192.30	1.00	0.00*	0.64
1c: Foam surface, feet together, eyes open	0.99 ± 0.02	1.05 ± 0.02	0.84	0.00*	0.00*	20.82 ± 14.20	21.27 ± 14.59	0.98	0.00*	0.63	2.088 ± 64.40	3.366 ± 68.88	1.00	0.00*	0.44
2a: Foam surface, feet together, eyes closed	0.99 ± 0.02	1.05 ± 0.02	0.83	0.00*	0.00*	19.56 ± 14.13	19.54 ± 12.83	0.99	0.00*	0.96	-22.86 ± 57.57	-23.67 ± 59.79	1.00	0.00*	0.27
2b: Hard surface, feet tandem stance	1.00 ± 0.01	1.05 ± 0.02	0.75	0.00*	0.00*	26.62 ± 16.35	24.81 ± 15.82	0.97	0.00*	0.15	-17.87 ± 58.80	-18.56 ± 62.09	1.00	0.00*	0.52

4. Discussion

This study investigated use of a new Open Movement IMU device/wearable (AX6) as a suitable tool within instrumented physical capability assessment for younger adults in a low-resource setting. Outcomes from the AX6 were compared to those from previously validated reference (AX3) and manual recordings. Our hypothesis was shown to be correct as this study showed good to excellent agreement between the AX6 and reference device across most tasks for accelerometer-based outcomes. Gyroscope data were robust for providing additional insights relating to turning detection during locomotion-based tasks. Findings suggest that the AX6 is a suitable digital tool for use in low-resource settings to quantify physical capability tasks. The AX6 (and AX3 reference) can capture robust raw data transparently, an emerging research priority (Alan Godfrey et al., 2021; Stern & Marra, 2019).

4.1 Locomotion (four-meter walk test)

On average, the AX6 (4.89s ± 0.76) recorded slightly lower times (0.15s) compared to the reference (5.04s ± 0.87). This is despite both devices utilizing the same algorithm to identify IC and FC times to estimate total time. The slight discrepancy may be from wearable placement, both placed laterally near L5. Visual examination showed slight variations in accelerometer signals (raw data). This was perhaps due to the left and right placement along/on the L5 vertebrae. Additionally, the AX6 uses a different inertial sensor (BMI160) compared to the AX3 (ADXL345). Perhaps differences in sensor manufacture contribute to slight signal deviations, impacting end values here as well as in all physical capability tests. Given slight signal discrepancies may arise between sensor signals (BMI160 vs ADXL345), these could be exacerbated by their differing attachment location. Thus, use of different wavelet scale parameters could improve signal to noise ratio without losing resolution enhancement (Shao & Ma, 2003) for different sensor types and wear locations, warranting future investigation. Different wavelet approaches have been examined elsewhere. For example, previous work examined a plethora of wavelet approaches for one aspect of physical functioning (i.e., postural transitions) noting possible accuracy improvement through careful wavelet type selection (Hickey, Galna, Mathers, Rochester, & Godfrey, 2016). Here, a CWT with a Gaussian wavelet function was used for the purposes of detecting IC and FC events within the gait cycle. Alternatively, it has been proposed that IC and FC accuracy could be improved by using a bi-orthogonal spine wavelet (A. Godfrey, Del Din, et al., 2015; A. Godfrey, Lara, Munro, et al., 2015).

Timing differences was over 0.7s between the AX6 and manual recordings. Large discrepancies and significant difference is primarily due to the subjective nature of manual assessment and errors within researcher timing on correctly identifying initial as well as final contact to signify the start and end of the trial, respectively. This is similar to previous discussions (A. Godfrey, Lara, Munro, et al., 2015).

4.2 Lower limb strength (sit-to-stand)

The AX6 showed slightly longer duration compared to reference, however these were not significantly (p=0.05) suggesting comparable results as demonstrated previously (A. Godfrey, Lara, Del Din, et al., 2015). There were significant differences (p=0.02) between the AX6 and manual observation (trial 2). This could be attributed to observer/researcher error and variability in start and stop times of the test, which can be biased and influenceable by subjective opinion (Cooper et al., 2011; Cooper, Kuh, Hardy, & Mortality Review, 2010; A. Godfrey, Lara, Del Din, et al., 2015). Previous work investigated accuracy of algorithms and wavelets in different sensor placements on the body (A. Godfrey, Barry, et al., 2014). As described by the referenced study, change of wearable location to suit the momentum transfer strategy (often used by manual observers) would likely optimize agreement, but impact negatively on agreement in other tasks within the physical capability battery such as endurance walking test (A. Godfrey, Barry, et al., 2014).

4.3 Lower limb strength and locomotion (TUG)

In general, there were no differences (p=0.55) between AX6 (6.44s ± 1.00) and reference (6.30s ± 0.92). Similarly, there were no differences between average AX6 and average manual observation (6.24s ± 0.73, p=0.45). Manual observation was slightly shorter (6.24s ± 0.73) than the AX6 (6.44s ± 1.00), this may be due to the way the TUG test was administered, whereby the researcher faced participants and did not suitably observe truck flexion at the start and end of the chair rise and sit. Under manual observation, TUG start time is observed when the participants back of their legs leaves the chair and finishes when the back of legs re-touch the chair. Future work utilizing the AX6 gyroscope sensor should segment TUG into sub-components for more informed SRC assessment i.e., sit to stand and gait/turning, which would streamline previous multi wearable attachment methodology (Salarian et al., 2010).

4.4 Endurance (2-minute walking task)

Compared to manually recordings, both wearables underestimated total distance. There are some key issues pertaining to the difference of total distance walked during this test. The inverted pendulum model is optimized for straight line linear walks only (W. Zijlstra & Hof, 1997; Wiebren Zijlstra & Hof, 2003). Authors of the proposed model

describe how the center of mass and pelvic displacement approximately correspond to sinusoidal movement patterns. However, the underlying pattern of acceleration during walks in our protocol would not have been linear and so could not be perfectly modelled by a sinusoidal function. That would have been further impacted by the directions given to participants, i.e. walking as fast as they could, where walking speeds would have fluctuated during all endurance walks due to e.g. fatigue. Moreover, inconsistent angular changes (left or right turns) during which participants rounded ends of the 10m course would negatively impact functionality of the inverted pendulum model. That is because wearables placed on either side of the vertebrae would experience different biomechanical properties of foot placement of up to many centimeters which would accumulate into many meters over the duration of a 2min walk. Thus, linear acceleration and wearable placement will not have been perfectly described by a sinusoidal function here. When the raw acceleration signals were examined, we observed that not all IC/FC events were suitability identified at the moment of a turn (identified from raw gyroscope data) which negatively impacted the algorithms' ability to correctly estimate steps length compared to straight line walking. This may have been attributed to location around L5 and direction of turning at the end of each walk. Further examination of the AX6 gyro data revealed that it correctly quantified total number of turns (left or right) compared to manual calculations.

Although the AX6 (140.57m ± 16.01) compared to wearable reference (133.85m ± 15.42) showed statistically significant differences ($p<0.01$), the mean difference was approx. 6.7m with a 95% confidence interval (3.6m to 9.9m). With total walking distances ranging from 115m to 170m, this degree of accuracy may be deemed suitable, especially as the protocol involved walking back and forth. However, such accuracies should be investigated as to their suitability in examining individual performance variation/change due to e.g., mTBI in a sporting context. Significant differences between AX6 and manual recordings (196.67m ± 19.72) can also be attributed to the protocol adopted here. The AX6 sensor being sensitive to linear deviations of gait (rounding/turning past the cones) and wide movement path around cones, which may negatively impact on peak detection accuracy and subsequent IC/FC estimations. Clearly asking participants to complete the task in a linear fashion with 180-degree may help to overcome these overestimations, but this would limit the clinical relevance and ecological validity as humans naturally complete lots of turns or rarely walk in a straight line (Stuart et al., 2020). Nevertheless, current use of existing wearable algorithms to quantify step length with any walking protocol would suggest useful proxy values as outcomes to gauge total distance walked.

4.4.1 Spatial and temporal gait

There were no significant differences between the AX6 and reference device for temporal gait outcomes or velocity derived. Although the spatial outcome (step length) was significantly correlated, there was a significant difference between mean values. Again, this can be attributed to the reasons highlighted in section 4.1 i.e., inverted pendulum model and protocol used.

4.5 Standing balance

Research has shown that using IMU derived standing balance data to be optimal and consistent with postural control digital biomarkers quantified using traditional laboratory tools (A. Godfrey, Lara, Munro, et al., 2015; Whitney et al., 2011). Digital biomarkers quantified in this study are similar to those quantified previously (Mancini et al., 2012). However, values presented here are higher due to the deliberate inclusion of tri-axial data compared to one (i.e., mediolateral, or anteroposterior only). This was to examine wearable response for changes of movement according to varying balance test. We found no significant differences and good correlation for Sway and Jerk (Table 4). Contrastingly, there were significant differences between AX6 and reference for RMS across all trials, albeit with moderate to good correlation and with minimal absolute difference (0.05 – 0.06mm.s^{-2}), Table 4. This can be attributed to RMS calculation, where differences in raw (sample level, due to different sensors BMI160 vs ADXL345) data remain evident compared to examining derivative and trigonometric variations (e.g., Jerk and Sway). Previous research highlights challenges of reliable comparison to postural control data from other literature (A. Godfrey, Lara, Munro, et al., 2015). That study also utilized male university adults from contact sport which may exhibit different gait and balance profiles to other young healthy adults who do not play contact sports (Black et al., 2020; Fuller, Govind, Tucker, & Raftery, 2018). Future standing balance work should carefully perform a full system check/disclosure of all underlying sensor types to account for differences (or agreements) between outcomes to ensure clarity for smart health diagnostics. This could be pertinent when trying to find difference in SRC (or other clinical population).

4.6 Limitations and future work

Although beyond the scope/aims of this study, a future recommendation would be for an analytical validation to be performed via suitable bench testing approaches to thoroughly investigate raw data from both devices. For example, a previous approach compared the acceleration output of an ADXL202 to a potentiometer within a pendulum-based device (A. Godfrey, Hourigan, & O'Laighin, 2007). The referenced study used a bench top rig (ADXL202 embedded within the center of a pendulum mass and compared output to the rotating shaft of a potentiometer from which the pendulum was suspended) to subject the accelerometer to a known repeatable, varying acceleration signal similar to that experienced in gait. Such an approach aids verification approaches to device/sensor suitability for motions similar to physical capability (Sliepen & Rosenbaum, 2016).

Future work should include a larger and more substantial sample size to increase variability in participant data. Moreover, this study was conducted on young, fit healthy males only. Similar studies examining use of the AX6 should examine the device between genders as well as on older adults with pathology to determine the wearables suitability/fit-for-purpose in e.g., frail cohorts, where suitability of inertial data thresholds would need to be investigated and established. Here, we aimed to assess the usefulness of the AX6 to generate accelerometer-based physical capability outcomes in young adults in a low-resource setting while determining if its gyroscope could supplement assessment. Going forward, the AX6 (accelerometer and gyroscope data) should be examined for its suitability to better quantity digital data biomarkers for clinical validity across a range of e.g., gait and turning outcomes. Indeed, use of the gyroscope sensor could help automated segmentation of all tasks.

5. Conclusion

This study investigates the use of a new Open Movement IMU (AX6) for physical capability assessments in young adults within a low-resource setting. Compared to a well validated reference, good to excellent agreement for accelerometer-based outcomes were found. Additionally, the AX6 gyroscope was useful and robust for turning detection, augmenting accelerometer data. Findings suggest the low-cost AX6 is a suitable digital tool to provide accessible and robust raw data for to quantify physical capability in a low-resource setting. This is important as the fields of digital health and digital medicine seeks transparent and robust methods of assessment. Although our sample size was small, this suggests the AX6 may be scalable for data collection on larger studies in community environments.

Data

Data will be made available upon reasonable request from corresponding author.

Conflict of interest

There is no conflict of interest.

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