This is the published version of a paper published in *Journal of Biomechanics*.

Citation for the original published paper (version of record):


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Validation of algorithms for calculating spatiotemporal gait parameters during continuous turning using lumbar and foot mounted inertial measurement units

Alexander Kvist, Fredrik Tinmark, Lucian Bezuidenhout, Mikael Reimeringer, David Moulaee Conradsson, Erika Franzén

Division of Physiotherapy, Department of Neurobiology, Care Sciences and Society, Karolinska Institutet, Stockholm, Sweden
Medical Unit Occupational Therapy & Physiotherapy, Women’s Health and Allied Health Professionals Theme, Karolinska University Hospital, Stockholm, Sweden
Karolinska University Hospital, Motion Analysis Laboratory, Stockholm, Sweden
Department of Physiology, Nutrition and Biomechanics, The Swedish School of Sport and Health Sciences, Sweden

ARTICLE INFO
Keywords:
Turning
Walking
Inertial measurement unit
Gait
Validation

ABSTRACT
Spatiotemporal gait parameters such as step time and walking speed can be used to quantify gait performance and determine physical function. Inertial measurement units (IMUs) allow for the measurement of spatiotemporal gait parameters in unconstrained environments but must be validated against a gold standard.

While many IMU systems and algorithms have been validated during treadmill walking and overground walking in a straight line, fewer studies have validated algorithms during more complex walking conditions such as continuous turning in different directions.

This study explored the concurrent validity in a population of healthy adults (range 26–52 years) of three different algorithms using lumbar and foot mounted IMUs to calculate spatiotemporal gait parameters: two methods utilizing an inverted pendulum model, and one method based on strapdown integration. IMU data was compared to a Vicon twelve-camera optoelectronic system, using data collected from 9 participants performing straight walking and continuous walking trials at different speeds, resulting in 162 walking trials in total. Intraclass correlation coefficients (ICC) for absolute agreement were calculated between the algorithm outputs and Vicon output.

Temporal parameters were comparable in all methods and ranged from moderate to excellent, except double support time which was poor. Strapdown integration performed better for estimating spatial parameters than pendulum models during straight walking, but worse during turning. Selecting the most appropriate model should take into consideration both speed and walking condition.

1. Introduction
Estimating spatiotemporal gait parameters allows for objective measurement of gait performance. These parameters are useful for determining factors of health and physical function (Dommerhuijsen et al., 2020; Hollman et al., 2011) and disease (Sofuwa et al., 2005). Laboratory-based systems used for measuring gait parameters, such as optoelectronic systems (e.g., Vicon motion capture) or instrumented walkways (e.g., GAITRite), are often constrained to use in dedicated movement laboratories or only allow for a limited range of walking. Inertial measurement units (IMUs) allow for the study of unconstrained walking in a wider range of environments in an ecologically valid state which better reflects walking in daily living. However, measurements from such IMUs must be validated against a gold standard (e.g., optoelectronic systems).

While several studies have validated IMUs for steady state walking on treadmills or in a straight line (Del Din et al., 2016; Washabaugh et al., 2017; Zijlstra and Hof, 2003) generally showing high agreement with gold standard (Del Din et al., 2016; Washabaugh et al., 2017), few have validated more complex conditions reflecting daily living, such as walking while turning. In fact, up to as many as 45 % of steps during typical daily living are turning steps (Glaister et al., 2007). Being able to

* Corresponding author.
E-mail addresses: alexander.kvist@ki.se (A. Kvist), erika.franzen@ki.se (E. Franzén).

https://doi.org/10.1016/j.jbiomech.2023.111907
Accepted 13 December 2023
Available online 19 December 2023
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accurately measure turning steps is also important in disease, for example in Parkinson’s disease where more than half of people in mild to moderate stages of the disease report turning problems (Bloem et al., 2001; Nieuwboer et al., 1998).

Calculating spatiotemporal gait parameters using IMUs generally consists of two separate parts: first identifying gait events such as heel-strike (HS) and toe-off (TO) to estimate temporal parameters such as step time, then estimating spatial parameters such as step length (Bertoli et al., 2018). Methods for identifying gait events can be categorized within peak-detection methods (e.g., in gyroscope data or wavelet-differentiated signals), template matching, or machine learning (Hajighasemi et al., 2018). Estimating spatial parameters using IMUs is generally done using some form of biomechanical model (Lueken et al., 2021; Zijlstra and Hof, 2003), machine learning (Guimarães et al., 2021; Hannink et al., 2018; Sharifi Renani et al., 2020), or strapdown inertial navigation methods (Mannini and Sabatini, 2014) also used in pedestrian dead-reckoning systems (Bebek et al., 2010; Khedr and El-Sheimy, 2021). These generally require a combination of inertial positioning with additional assumptions about underlying motion (Wahlström and Skog, 2021) to constrain position error. Determining position from acceleration containing systematic errors is an operation introducing a cubically growing position error (Foxlin, 2005) with a significant error source being the estimation of the orientation of the sensor (Carlsson et al., 2022). Furthermore, since position error grows with time (Foxlin, 2005), it could be expected that selected walking speed (with its relationship to e.g., step time) could have an influence on estimation accuracy, especially slower speeds.

The aim of this study was therefore to investigate the agreement to gold standard of several different algorithms for calculating spatiotemporal gait parameters using measurements from IMUs obtained during both straight walking and walking while turning, at several different walking speeds. The validation study was carried out in a movement analysis laboratory at Karolinska University Hospital, Sweden. The study was approved by the Swedish ethical review authority (Dnr 2020-03059 and 2020-05315). All participants received verbal and written information and gave written consent prior to study participation.

A total of 9 healthy participants (5 females, age 39.9 ± 8.3 years, weight 71.6 ± 13.1 kg, length 172.3 ± 13.2 cm) without movement impairments were equipped with IMU sensors with triaxial accelerometer, gyroscope, and magnetometer (APDM; Opal, Portland, US) positioned on the lumbar and feet (Fig. 1b). Subjects were asked for their height. IMU data was recorded in the APDM Mobility Lab software (APDM, Portland, US). The algorithms using IMU sensors were validated against a 12-camera 3D capture system from Vicon Motion Systems Ltd (Oxford Metrics, UK). Sixteen reflective markers were positioned on the lower body (Fig. 1b) for use in the Conventional gait model (CGM1) (Leboeuf et al., 2019).

Each participant performed 3 trials of straight walking and 3 trials of walking with continuous turns (approx. 10 m), each at 3 different walking speeds. Target speeds were approximately 1.2 m/s, 0.9 m/s, and 0.6 m/s, and participants were asked to walk at a normal pace, slower, and significantly slower. Trials were controlled to not deviate too much from target speed.

The turning condition consisted of a track of cones with about 90° to 225° turns to the left and right. Participants were instructed to alternate between turning around yellow and orange cones, ignoring grey cones (Fig. 1a). The gait assessment resulted in a total of 18 trials per participant and 162 trials in total.

2.2. Data analysis

Spatiotemporal parameters from the Vicon system were calculated from heel markers by defining HS/TO events in Vicon Nexus 2.12 and exported using Vicon Polygon 4.4.5. All events were verified from frame-synchronized video. IMU raw data were exported from the Mobility Lab software in HDF5 format. Since the Vicon and IMU recordings were not precisely synced, lag between the signals was obtained by cross-correlation between the Vicon Z (vertical) position signal of the heel markers and the Opal sensor Z (vertical) acceleration signal. For gait event detection in all methods, recorded IMU data was cut to 1 s before the first event in the Vicon data (HS or TO) and 4 s after the last event in the Vicon data, taking into consideration the cross-correlation lag between Vicon and IMU signals. Cross-correlation of signals was performed in MATLAB (R2021a, MathWorks, US). All further analysis was performed in Python (v3.9.7).

Fig. 1. Experimental setup. Left (a): track of cones and walking path with Vicon camera system. Right (b): positioning of reflective markers (grey circles) and IMU sensors (blue squares). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
2.3. Method 1 – inverted pendulum using lumbar sensor

Using a single lumbar IMU sensor, HS and TO detection using continuous wavelet transform (CWT) was performed on anterior-posterior acceleration data based on Pham et al., (2017) (Fig. 2). Spatiotemporal gait parameters were calculated from timing of HS and TO as well as with an inverted pendulum model (IPM) (Del Din et al., 2016; Zijlstra and Hof, 2003).

2.3.1. Gait event detection

The gait event detection followed the procedure described in (Pham et al., 2017), with a few modifications that were found to perform better for this data. First, a gaus1 wavelet was used for both straight and turning trials instead of the gaus2 and db2 wavelets used originally (Pham et al., 2017). Second, peak selection limits of 20 % and 40 % for HS and TO respectively were used instead of 40 % for both used originally (Pham et al., 2017). Finally, HS had to be followed by TO, otherwise, the event was marked as invalid and the step cycle was not used in further calculations. Left and right gait events were assigned alternatingly. Wavelets were computed using the PyWavelets library (v1.4.1) (Lee et al., 2019).

Fig. 2. Gait event detection from an example trial. a) Illustration of gait events for the left and right leg. b) Gait event detection using the wavelet method, showing anterior-posterior acceleration (acc_ap) and first- and second-order wavelet-differentiated acceleration (dcwt1/2). c) Gait event detection using the gyroscope method for a single leg, showing gyroscope data (Gyro), and calculated heel-strike (HS), toe-off (TO), foot-flat (FF), and mid-swing (MS) events.
2.3.2. Vertical position estimation
To determine spatial parameters, vertical position during each step was determined for use in the IPM. First, acceleration signals $a_{body} = [\tilde{a}_{antereoposterior}, \tilde{a}_{mediodistal}, \tilde{a}_{vertical}]$ (represented by sensor axes x, y, and z respectively) were low-pass filtered using a 4th order Butterworth filter with cutoff frequency 4 Hz. Then, to obtain acceleration in a horizontal-vertical plane, $a_{body}$ was rotated around its second axis representing pitch, until the mean value $a_{vertical_stationary}$ of the first stationary part of $a_{vertical}$ showed its largest value. Gravity compensation was achieved by subtracting $[0, 0, a_{vertical_stationary}]$ from rotated acceleration. Vertical position was then estimated by double integration of acceleration between heel strikes and was then detrended by high-pass filtering with 0.1 Hz (4th order Butterworth filter) (Zijlstra and Hof, 2003).

2.3.3. Parameter calculation
Using the detected gait events, temporal parameters were calculated for each foot (formulas written for right foot, left foot changes start side) as (Salariian et al., 2004):

\[
\text{Step time} = HS_i(i + 1) - HS_i(i) + 60
\]

\[
\text{Cadence} = \frac{1}{\text{Step time}} \times 60
\]

\[
\text{Single support} = HS_i(i) - TO_i(i)
\]

\[
\text{Double support} = TO_i(i) - HS_i(i) + TO_i(i) - HS_i(i)
\]

where $HS_i(i)$ is right HS followed by left HS $HS_i(i)$ for gait cycle $i$ and similarly for TO.

Spatial parameters were estimated using an IPM (Del Din et al., 2016) as:

\[
\text{Step length} = 2\sqrt{2l \times h^2}
\]

\[
\text{Walking speed} = \frac{\text{Step length}}{\text{Step time}}
\]

where $l$ is estimated by subject height*0.53 and $h$ is the change in vertical position during a step.

2.4. Method 2 - inverted pendulum using foot and lumbar sensors
Gait events were determined from the gyroscope signal from the foot-mounted IMUs (Fig. 2), and the IPM was applied to lumbar IMU data as in method 1.

2.4.1. Gait event detection
Gait events (HS, TO and foot-flat, FF) were obtained by using a gyroscope signal peak detection method based on Salariian et al., (2004) and Mariani et al., (2010). The z-score normalized gyroscope signal representing pitch of the foot sensor (i.e., around the y axis) $\tilde{gyro}_y$ was used. First, mid-swing points were identified by finding the maxima of $\tilde{gyro}_y$ (minimum height 1.0, minimum distance 0.5 s). To identify HS and TO, each segment of 1.5 s before and after each mid-swing point was searched. Segments were smoothed with a low-pass order 48 FIR filter, with cut-off frequency 30 Hz. The first local minimum (minimum height 0.1) after mid-swing was taken as HS. The first minimum before mid-swing was taken as TO (minimum height 1.0, minimum distance 0.15 s). Finally, during stance (from HS to TO), FF time instants were identified as the middle of the FF phase of each foot, with FF phase defined as the time points when $|\tilde{gyro}_y| < 0.2$.

2.4.2. Parameter calculation
Parameters were calculated as in method 1.

2.5. Method 3 – Strapdown integration using foot sensors
Gait parameters were estimated using foot sensor data, using a strapdown integration, 3D position estimation method (Mannini and Sabatini, 2014; Mariani et al., 2010; Muthukrishnan et al., 2020; Rampp et al., 2015; Rebula et al., 2013; Sabatini et al., 2005; Shah et al., 2022; Trojaniello et al., 2014). Gait event detection was the same as in method 2.

2.5.1. Orientation estimation
Gyroscope, acceleration and magnetometer signals were low-pass filtered using a 4th-order Butterworth filter with cutoff frequency 4 Hz. To determine the orientation of each sensor in a global frame, a Madgwick orientation filter (Madgwick et al., 2011) was used with gain $\beta = 0.041$ as recommended for MARG arrays, using the AHRS Python library (v0.3.1). The resulting orientation quaternion for each sensor $q_{sensor}$ was defined in an east, north, up (ENU) frame (Fig. 3). An approximate initial orientation $q_0$ was used to initialize the gradient descent of the filter for all trials, based on the accelerometric estimate (Trimpe and D’Andrea, 2010) of one participant’s stance before initiating walking, as implemented by AHRS.

2.5.2. Position estimation
Using orientation quaternion $q_{sensor}$, acceleration signal $a_{body}$ was rotated into a global frame acceleration $a_{global}$ by rotating with the inverse of $q_{sensor}$. Gravity compensated acceleration $a_{grav}$ was obtained by subtracting acceleration vector $a_{gravity} = [0, 0, g]$ from $a_{global}$. Orientation estimates during turning were found to have a certain amount of drift, causing deviations in estimated vertical position. To compensate for this, vertical acceleration $a_{grav}$ was adjusted by a linear resetting function similar to Anderson et al., (2018) between foot-flat time points $t_{ff}+1$ and $t_{ff}$ as:

$$ h_0(a_{grav}(t)) = \frac{t_{ff} - t}{t_{ff} - t_{ff}+1}a_{grav}(t) \quad \text{where} \quad t_{ff}+1 \leq t \leq t_{ff} $$

Resulting adjusted acceleration $a_{adjusted}$ was then integrated between $t_{ff}+1$ and $t_{ff}$, yielding velocity. To prevent drift in estimated velocity, a zero-velocity update (ZUPT) was applied by linearly de-drifting (Rebula et al., 2013) between foot-flat instants, assuming that velocity is zero at each $t_{ff}$. Linearly de-drifted velocity was integrated again to yield positions of the sensors over time. Trajectories of the sensors could then be reconstructed (Fig. 4).

2.5.3. Parameter calculation
Temporal parameters were calculated as in method 1, but with additionally:

\[
\text{Stride time} = t_{ff}+1 - t_{ff}
\]

Using estimated positions of the sensors, stride length and walking speed were calculated. To calculate stride length, a stride vector and a local heading direction (Rebula et al., 2013) were defined between three consecutive FF as:

\[
\text{stride} = \text{pos}(t_{ff}+1) - \text{pos}(t_{ff})
\]

\[
\text{heading} = \text{pos}(t_{ff}+2) - \text{pos}(t_{ff})
\]

For the last strides, the last FF position was used to define the heading direction. Using the heading direction vector, scalar projection of the stride vector in the heading direction was used as stride length.

$$ \text{Stride length} = \frac{\text{stride} \cdot \text{heading}}{|\text{heading}|} $$
Walking speed = \frac{\text{Stride length}}{\text{Stride time}}

During turning trials, especially at lower speeds, estimated trajectories had some unstable strides. Valid strides were counted as strides where \(0 \leq \text{stride length} \leq 2\text{m}\), to avoid negative values and values unlikely during regular walking.

2.6. Statistical analysis

Intraclass correlation coefficients ICC\(_{a,1}\) were calculated for absolute agreement between Vicon and IMU measurements (mean of gait cycles...
in a trial) for trials at each different speed using the Pingouin library (v0.5.2) (Vallat, 2018). Limits of poor, moderate, good and excellent agreement were set according to Koo and Li (2016) (Koo and Li, 2016) as follows: below 0.50: poor, between 0.50 and 0.75: moderate, between 0.75 and 0.90: good, above 0.90: excellent.

3. Results

Mean temporal and spatial gait parameters for Vicon and IMU measurements are shown in Fig. 5. Step time had high agreement with the Vicon values in all methods except for one outlier in method 1, while step/stride length had lower agreement. In the IPM methods (method 1 & 2) step length and walking speed were generally underestimated in straight walking trials, but overestimated in turning trials. The strap-down integration method (method 3) generally performed better for all variables in straight walking trials than turning trials. Box plots for other variables can be found in the supplementary material.

ICC values for all methods can be seen in Fig. 6. A table of all ICC values as well as mean differences between the systems can be found in the supplementary material.

3.1. Method 1 (Inverted pendulum using lumbar sensor)

Cadence and step time (except for step time at 1.2 m/s due to an outlier) had excellent agreement for both straight and turning trials at all speeds. Single support had good to moderate agreement, but double support had poor agreement (except turning at 0.6 m/s trials). Walking speed had moderate to poor agreement, with turning at 1.2 m/s and straight at 0.6 m/s having poor agreement. Step length had poor agreement for all trials, the worst being trials at 0.6 m/s.

3.2. Method 2 (Inverted pendulum using foot and lumbar sensors)

Cadence and step time had excellent agreement for all trials. Single support had good to moderate agreement, turning trials having higher agreement. Double support had poor agreement in all trials. Walking speed had moderate agreement in all trials. Step length had poor agreement except for straight trials at 1.2 m/s which had moderate agreement. Turning trials generally had better agreement than straight trials.

3.3. Method 3 (strapdown integration)

Temporal variables (step time, cadence, double and single support)

Fig. 5. Box plots for step time, step/stride length, and walking speed (left to right: method 1, 2, and 3. Blue shaded area: straight trials. Green shaded area: turning trials). Boxes extend from lower to upper quartile, with a line at median. Whiskers extend to 1.5 times the interquartile range (IQR). Outliers are individual points. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
Spatial parameters (walking speed and stride length) had significantly better agreement for straight walking trials where walking speed had good to moderate agreement and stride length had moderate agreement. The ICC values for straight walking trials were comparable to values extracted from Mobility Lab’s algorithm (available in supplementary material) except for single/double support. For turning trials, walking speed had moderate to poor agreement, and stride length had poor agreement in all trials.

4. Discussion

In this validation study, we tested 3 different methods for calculating spatiotemporal gait parameters using lumbar and foot IMU sensors, validating them against a twelve-camera optoelectronic system (Vicon) acting as gold standard.

Detected gait events were comparable for both the wavelet method with data from the lumbar sensor (method 1) and using the gyroscope signal of the feet sensors (method 2). This could be useful for studies only interested in basic temporal parameters such as step time, given the practicality of using one sensor compared to two. Temporal parameters generally had high agreement except for double support time which had
poor agreement. The poor agreement could be due to double support time relying on gait events on both feet being accurate. Parameters relying on accurate information from both feet have been shown to have higher errors in earlier studies using IMUs (Teufel et al., 2018).

Spatial parameters are important for studying gait, with some being especially important for certain populations, such as stride length in Parkinson’s disease (Morris et al., 1998). Walking speed, which is based on step/stride length, is also an important overall marker of health (Dommershuijzen et al., 2020). In this study, step length generally had low agreement for the pendulum models, underestimated the values in straight trials and overestimating them in turning trials. The underestimation has also been observed in Zijlstra and Hof (2003) for straight walking. However, the differences between gold standard and IMU for step length and walking speed were larger in this study than in Del Din et al., (2016) which compared a pendulum model to an instrumented walkway as gold standard. This could be due to different systems being used, or that this study used specific gait speeds and not self-selected gait speed.

During straight walking, the lower gait speeds had lower step/stride length agreement. This is likely due to the time of the integration span. The accuracy of the double integration estimate decreases with time (Foxlin, 2005), so a slower walking speed with a longer step/stride time will have a larger error.

Stride lengths from the strapdown integration methods for straight walking can be compared to Mariani et al., (2010), Rebula et al., (2013), Trojaniello et al., (2014) who found differences within 1 to 1.4 %, although the largest mean difference was 1.53 % in this study. The results for the turning trials at different speeds are novel and we could not find much comparable data, except for a few studies (Mariani et al., 2010; Shah et al., 2022). One study (Mariani et al., 2010) reported that errors between calculated IMU parameters and gold standard did not differ much during an 8-turn task, compared to straight walking. In our data, while the difference of mean values for turning trials was small for 0.9 and 1.2 m/s (<4%), the ICC was still low, and the error increased (15 %) and ICC dropped significantly for slower trials.

In general, while the strapdown integration method performed better in straight trials, it performed worse in turning trials. Additionally, extra assumptions had to be imposed during turning trials. So, while the strapdown integration method resulted in acceptable agreement for straight walking trials, it is possible that sensitivity to orientation errors results in reduced agreement during turning. The used Madgwick orientation filter has a higher error in the heading axis as compared to the other axes, and the error in dynamic roll estimation is higher than the pitch (Madgwick et al., 2011). Furthermore, the magnetometer which is used to compute heading has a relatively high noise density as compared to the other sensors according to the APDM technical specifications. Therefore, turning steps that rely on roll and heading (in addition to pitch) might be less accurate compared to straight steps mostly relying on pitch. Pendulum models seem less sensitive to such errors, resulting in at least moderate agreement for walking speed during turning trials.

This study measured healthy participants and gives an indication how performance of the algorithms shifts from straight walking to turning at different speeds. It should be expected that performance could vary somewhat in clinical populations. When evaluated in Parkinson’s disease, performance of some algorithms underlying this study has been shown to drop slightly (Del Din et al., 2016) or in some cases show similar levels of accuracy (Muthukrishnan et al., 2020; Pham et al., 2017; Trojaniello et al., 2014). Larger scale validation studies on multiple clinical groups from the Mobilise-D project (Micó-Amigo et al., 2023) have shown performance of various algorithms to either increase or decrease compared to healthy adults, depending on group. Recent validation datasets on diverse gait tasks in clinical populations (Warmerdam et al., 2022) could be used in future studies to investigate such changes.

Results from this study are generally consistent with findings from the Mobilise-D project, where larger errors for stride length are observed for slow walking speeds (Micó-Amigo et al., 2023), and generally when comparing more complex walking activities compared to simple straight walking (Salis et al., 2023).

A limitation of this study is a lack of precisely synchronized triggers. Although signals were synchronized via cross-correlation, it is difficult to verify if the IMU algorithms might have captured false-positive gait events or missed some gait events at the start or end of the data. The exact timing of gait events on a time axis could not be compared, which could have enabled more detailed analysis. Finally, there could be several untested tuning parameters that could result in better outcomes.

No single algorithm performed the best for every parameter in both turning and straight walking at each speed. Strapdown integration performed better for calculating spatial parameters during straight walking than the IPM. For turning, detecting events from foot sensors and obtaining spatial parameters via IPM performed better. Gait speed had an impact on accuracy, especially on spatial parameters. Parameters could be calculated with moderate to excellent agreement in all conditions (both turning and straight walking, from 0.6 m/s to 1.2 m/s) except for stride/step length in turning trials and double support in all trials. Thus, when selecting the most appropriate model to calculate spatial and temporal gait parameters it is important to take into consideration both walking speed and walking condition.

5. Data availability statement

Code is available via: https://github.com/alkvi/python-imu-gait-evaluation

With respect to the Swedish and EU personal data legislation (GDPR), the data are not freely accessible due to regulations regarding personal integrity in research, public access and privacy. The data are available from the principal investigator of the project: Erika Franzen (erika.fransen@ki.se), on a reasonable request. Any sharing of data will be regulated via a data transfer and user agreement with the recipient.

CRediT authorship contribution statement

Alexander Kvist: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Formal analysis. Fredrik Tinmark: Writing – review & editing, Methodology, Formal analysis, Data curation, Conceptualization. Lucian Bezuidenhout: Writing – review & editing, Methodology, Data curation, Conceptualization. Mikael Reimeringer: Writing – review & editing, Methodology, Formal analysis, Data curation. David Moulaee Conradsson: Writing – review & editing, Data curation, Conceptualization. Erika Franzen: Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

We thank all participants for making this study possible as well as the uMOVE core facility at Karolinska Institutet. This study was supported by grants from the Norrbacka-Eugenia foundation, the Doctoral School in Health Sciences and the Strategic Research Area in Health Care Sciences at Karolinska Institutet.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jbiomech.2023.111907.
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