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Reliability of waveforms and gait metrics from multiple outdoor wearable inertial sensors collections in adults with knee osteoarthritis

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ABSTRACT

Wearable sensors may allow research to move outside of controlled laboratory settings to be able to collect real-world data in clinical populations, such as older adults with osteoarthritis. However, the reliability of these sensors must be established across multiple out-of-lab data collections. Nine older adults with symptomatic knee arthritis wore wearable inertial sensors on their proximal tibias during an outdoor 6-minute walk test outside of a controlled laboratory setting as part of a pilot study. Reliability of the underlying waveforms, discrete peak outcomes, and spatiotemporal outcomes were assessed over four separate data collections, each approximately 1 week apart. Reliability at a different number of included strides was also assessed at 10, 20, 50, and 100 strides. The underlying waveforms and discrete peak outcome measures had good-to-excellent reliability for all axes, with lower reliability in frontal plane angular velocity axis. Spatiotemporal outcomes demonstrated excellent reliability. The inclusion of additional strides had little to no effect on reliability in most axes, but the confidence intervals generally became smaller across all axes. However, there was improvement in axes with lower (i.e., good) reliability. These data were collected in an out-of-lab setting, and the results are generally consistent with previous in-lab data collections, likely due to its semi-controlled nature. Additional out-of-laboratory research is required to investigate if these trends continue during truly free-living collections. This study provides support for increasing research conducted in out-of-lab data collections, as demonstrated by the good-to-excellent reliability of all axes.

1. Introduction

Osteoarthritis (OA) is a debilitating degenerative joint disease that affects nearly 20 % of all adults and more than 50 % of those over the age of 70 as a result of loss of cartilage and changes in the bone and soft tissues, often resulting in joint pain, mobility deficits, and a reduced quality of life, (Bombardier et al., 2011). The knee is the most commonly affected joint and often undergoes significant changes in the dynamic loading environment and movement patterns during walking gait (Andriacchi and Favre, 2014; Kaufman et al., 2001). Conventional gait analysis systems are often used to study kinematic and kinetic factors with respect to disease progression (e.g., knee adduction moment) and treatment (e.g., knee flexion angle) (Bonnefoy-Mazure et al., 2020; Chehab et al., 2014; Simic et al., 2010) but their impact outside of research has been limited given the accessibility of these systems for clinical gait analysis of OA.

Wearable inertial sensors offer an affordable and more broadly deployable alternative to collect gait data on those with knee OA (Gianzina et al., 2023; Rose et al., 2022). Moreover, these data can be collected in more ecologically valid, real-world settings outside of the conventional laboratory environment (Brodie et al., 2016; Hillel et al., 2019). These devices have the ability to measure gait parameters associated with knee OA progression, including spatiotemporal parameters (e.g. step time), segment angular velocity, and impact accelerations, and can do so over longer periods of time to improve how we diagnose and treat older adults with OA (Kobsar et al., 2020b). While acceleration and angular velocity-based metrics from wearable sensors are not as well understood as knee adduction moment and knee flexion, they have shown promise in their association to these metrics (Youn et al., 2018), as well as assessing TKA recovery (Christiansen et al., 2015; Turcot et al., 2008), and the presence of OA or OA symptoms (Khan et al., 2013; Liikavainio et al., 2010; Na and Buchanan, 2019). Further, more research is now integrating these accelerometer and gyroscope data as inputs for more complex artificial intelligence, data driven models for obtaining gait-related outcomes (Bacon et al., 2022; Tan et al., 2022; Wang et al., 2020). Therefore, the reliability of the underlying data

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derived from wearable sensors, especially in free-living collections, are important for a variety of use cases.

Despite the increased use of these sensors for gait analysis research, most data collections still occur in highly controlled laboratory settings under the direct supervision of the researcher (Kobsar et al., 2020b). These laboratory-based collections often lack real-world relevance and results obtained in-lab may not be equivalent to daily out-of-lab walking patterns. For instance, Brodie, et al., demonstrated that gait data from wearable sensors collected in-lab was different from that of free-living, with free-living data having a lower cadence and higher step time variability (Brodie et al., 2016). Similarly, Hillel, et al., showed that in-lab dual-task walking (e.g., walking while verbally completing math problems) in older adults was a better approximation of out-of-lab walking than a standard in-lab walking assessment (i.e., single task (Hillel et al., 2019)). Therefore, while the reliability of wearable inertial sensors has been studied extensively in-lab (Kobsar et al., 2020a, Kobsar et al. (2016)), the reliability of sensors in out-of-lab environments is still largely unknown. For example, discrete peak outcome variables are largely unknown in out of lab settings. These outcome variables are of particular interest as they could be used as proxies for gait parameters indicative of knee OA severity (e.g., peak frontal plane angular velocity as a proxy for varus thrust). Similarly, reliability studies are most often completed in healthy younger adults, limiting their applicability to populations of older adults with osteoarthritis where pain and fluctuations in pain are prevalent (Kumar et al., 2015; Leardini et al., 2014; Parry et al., 2017; Robert-Lachaine et al., 2017, p.), there is a clear gap in the literature and the need to assess the out-of-lab reliability for wearable sensors over multiple sessions in adults with knee osteoarthritis, before the unique advantages of wearable inertial sensors can be fully utilized. Therefore, the purpose of this pilot study was to evaluate the reliability of wearable sensor data collected across multiple days in out-of-lab settings in a knee OA population. To achieve this, we aimed to assess reliability of the acceleration and angular velocity waveforms obtained from the inertial sensors, as well as discrete impact peaks and spatiotemporal parameters over the course of four separate data collections. Additionally, as a simulation of the number of strides that are typically captured in a lab setting (e.g., 10–20 strides) as compared to out-of-lab collection (e.g. $>$ 50), we aimed to investigate if additional strides accumulated in a single walk could improve reliability across these collections by evaluating the use of the first 10, 20, 50, and 100 strides. It was hypothesized that waveform and spatiotemporal reliability would remain stable as stride inclusion levels increased, but discrete peak reliability may be improved with more strides, as OA gait may be more variable compared to normal gait and hence discrete variables may be more stable if they are based on a greater amount of strides.

2. Methods

2.1. Participants

As part of a larger study, nine older adults (64.2 $\pm$ 7.8 years) with moderate-to-severe knee OA were recruited from an orthopedic clinic four weeks prior to receiving an intra-articular knee injection (Table 1). The study was designed to be a within-subject reliability design with four repeated measures and reliability coefficients estimated at 0.90 with 95 % confidence interval at 0.2, yielding a required sample size of n = 10 (Shoukri et al., 2004). While recruiting more participants would have ultimately allowed for greater power and smaller confidence intervals, restrictions due to COVID-19 restrictions and weather conditions limited this work to a total of 9 participants (7 male, 2 female). Inclusion criteria required participants to be able to walk for 6 min without assistive devices, have an average knee pain of $>$ 3/10 on a visual analog scale at time of recruitment, uni- or bilateral OA, no previous lower limb joint replacements, and have no other physical or cognitive impairments affecting gait. The Research Ethics Board approved the study (HiREB 13247), and all participants provided their informed consent before entering the study.

Table 1
Patient Demographics.

	MEAN (STANDARD DEVIATION)
SEX (n)	7 Male, 2 Female
AGE (years)	64.2 (7.8)
MASS (kg)	92.0 (21.7)
HEIGHT (m)	1.72 (0.10)
BODY MASS INDEX (kg/m^2)	30.9 (5.4)
KELLGREN-LAWRENCE (KL) GRADE OF MOST AFFECTED KNEE (n)	KL1: 0 KL2: 3 KL3: 5 KL4: 1

2.2. Protocol

For each out-of-lab data collection, two 9-axis wearable inertial sensors (IMeasureU Blue Trident, 250 Hz, Vicon Ltd., Oxford, UK) were placed on each leg directly onto the skin at the anterior-medial aspect of the proximal tibia, identified by palpating anatomical landmarks, using semi-elastic straps (Fig. 1a). Sensors were strapped such the x-axis was aligned vertically with the long axis of the tibia and the positive y-axis was pointing medially on each side. A third sensor was attached at the lower back to calculate gait speed. While the IMU sensor used is capable of recording acceleration, angular velocity, and magnetic field, only the acceleration and angular velocity signals were analyzed for this study. Current pain level in the patient's knee joint was then assessed through a numerical pain rating scale (NPRS). Patients were instructed to complete an outdoor 6-minute walk at their self-selected pace at the same outdoor circuit located at the hospital (Fig. 1b). Patients were instructed to initially begin in a counterclockwise direction for the first lap and then walk free-living as they wanted to. Patients continued walking until an elapsed time of 6 min. Following the completion of the walk, the sensors were removed and data were downloaded for processing. This procedure was repeated for a total of four out-of-lab data collections, separated by at least 5 days (6.9 $\pm$ 0.8 days), with the final collection on the day of their intra-articular knee injection.

2.3. Data analysis

Following each collection, data were downloaded and uploaded to a secure server. Data from the sensors were stored locally on-device during collections and digitally synchronized between devices using the IMeasureU CaptureU app following the completion of data collection. Aligned sensor data were then processed using a custom MATLAB (Mathworks, Natick, MA, USA) script, beginning with applying a 4th order low pass Butterworth filter at 20 Hz to the data. Next, a principal component analysis (PCA) alignment correction, shown to improve axis alignment for in-lab straight walking (Hafer et al., 2020; Ruder et al., 2022), was applied to the data. Briefly, the PCA is used to align each axis in line with the segment it is attached to. As most acceleration during gait will be in the anterior-posterior axis (AP) direction, it can be assumed the first principal component (PC) will be related to the AP direction. Similarly, the second PC will be the next most acceleration in the vertical (V) direction. Finally, the third PC will be the remaining acceleration in the mediolateral (ML) direction. Because of the sensor attachment location on the tibia, while the V axis is aligned well, the signals from AP and ML axes are often mixed, resulting in not representative signal. This PCA method digitally rotates and aligns each axis to be more in line with the direction of motion of the segment of interest (i.e., tibia). Therefore, all references to axes following this step are aligned segment axes.

Data were parsed into individual strides for the left and right sides,

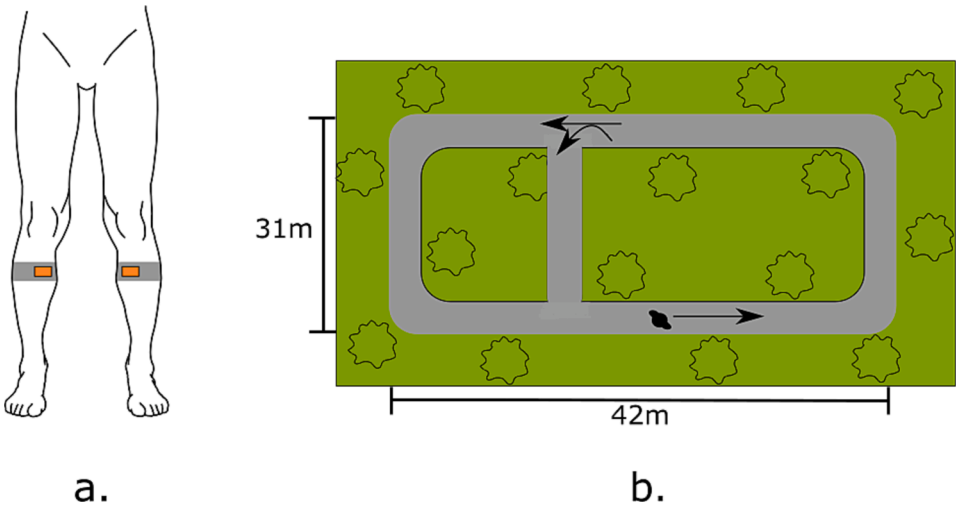

Fig. 1. Illustration of sensor placement and outdoor collection area.

respectively, and normalized to percentage of the gait cycle. For each collection, heel-strike and toe-off were identified using angular velocity from each sensors to segment the signal into individual gait cycles during stance for the duration of the 6-minute walk. Initial contact (i.e. heel strike) was found using the AP angular velocity zero-crossing after the mid-swing peak to identify a search window before using the accelerometer data to identify true initial contact, while toe-off similarly used the AP angular velocity zero-crossing in the second half of stance to approximate toe-off (Mariani et al., 2013). The signals from each individual gait cycle were normalized to 100 data points, representing percent of gait cycle, by interpolating each of the signals using the interp1 MATLAB function. Next, each individual acceleration and angular velocity axis at each point for each curve from 0 to 100 percent was averaged to create ensemble curves for all axes of interest. Positive linear acceleration impact peaks following initial contact during the first 25 % of stance for ML, V, and 3-dimentional resultant (R) acceleration were identified, while the negative peaks following initial contact during the first 25 % of stance were similarly identified for AP acceleration. Similarly for angular velocity peaks, positive frontal plane peaks during the first 25 % of stance were identified because of their relationship to estimates of varus thrust (Tsukamoto et al., 2021) and maximum absolute sagittal plane peaks during the first 25 % of stance were identified as reductions in sagittal plane measures have been associated with knee OA progression (Boekesteijn et al., 2022). However, the transverse angular velocities were not analyzed as they are not currently linked to any clinical outcomes (Kobsar et al., 2020b). For each collection day, ensemble curves, discrete gait variables (i.e., impact peaks), and spatiotemporal variables were obtained to assess the reliability of the wearable sensors across four collections. Gait speed was estimated by calculating stride length (eq. (1) and dividing by stride time. First, stride length was calculated using the inverted pendulum model, such that.

$$\text{Stride length} = 2\sqrt{2lh - h^2} \tag{1}$$

where h is change in vertical displacement of the center of mass of the truck and l is leg length, estimated by multiplying subject height by 0.5.

2.4. Statistical analysis

Reliability was assessed on ensemble waveforms, discrete peaks, and spatiotemporal variables. For each participant, comparisons were grouped by most affected and less affected side, as defined by Kellgren/Lawrence (K/L) grading of radiographic osteoarthritis (Kellgren and Lawrence, 1957). The reliability of the gait waveforms was assessed via the correlation of multiple correlation (CMC) (Ferrari et al., 2010) and also examined across the first 10, 20, 50 and 100 strides to understand how reliability changes with the inclusion of additional strides.

Similarly, the between day reliability of discrete peaks and spatiotemporal variables were assessed using an $ICC_{(2,k)}$. The $ICC_{(2,k)}$ was calculated for the first 10, 20, 50 and 100 peaks for the discrete peaks (i.e., mediolateral, vertical, anteroposterior, and resultant accelerations, frontal plane and sagittal plane angular velocity) and the spatiotemporal outcomes (i.e., stance time, swing time, stride time, and cadence). For both CMC and ICC, reliability was defined as $<$ 0.5, 0.50–0.75, 0.75–0.90, and 0.90 $+$ relating to poor, fair, good, and excellent, respectively. Mean and standard deviation (SD) were calculated for each discrete peak variable and spatiotemporal outcome 10, 20, 50 and 100 strides for each day. The standard error of the mean (SEM, eq. (3) (Rose et al., 2023) and minimal detectable change (MDC, eq. (3) (Washabaugh et al., 2017) were calculated as:

$$\text{SEM} = SD^*\sqrt{1 - ICC} \tag{2}$$

$$\text{MDC} = SEM\, x\, Z_n\, x\, \sqrt{2} \tag{3}$$

where SD is the standard deviation of all days for a given variable and Z_n corresponds to the Z-score for a given confidence interval. The MDC was calculated at 95 % and 80 % confidence intervals for each variable (MDC_{95} and MDC_{80}, respectively).

3. Results

Patients' K/L grade for the most affected knee ranged from 2 to 4 (Table 1). Five of nine patients had unilateral knee OA knee pain, while four of nine with bilateral knee OA pain had one knee rated as a worse K/L grade. Across the four study visits, patient reported NPRS pain ranged from 0 to 10 with an overall average of 5.3 $\pm$ 2.6, reflecting that pain levels were relatively stable between visits (Table 2). Similarly, gait speed across all four visits averaged 1.02 $\pm$ 0.16 m/s (mean absolute difference 0.17 m/s). Taken together, pain and gait speed were stable and therefore should not affect analysis of reliability.

For inertial sensor waveforms, reliability generally ranged from good-to-excellent for all axes (Table 3). ML acceleration demonstrated good reliability for both most affected ($CMC_{100} = 0.90$) and less affected limbs ($CMC_{100} = 0.87$). Frontal plane angular velocity waveform reliability ranged from 0.73 to 0.79 for both most affected and less affected sides. Including addition strides for frontal plane angular velocity resulted in a modest improvement towards good reliability (Fig. 2; most affected: $CMC_{10} = 0.75$, $CMC_{100} = 0.81$; less affected: $CMC_{10} = 0.73$, $CMC_{100} = 0.79$). V, AP, and R accelerations, in addition to sagittal plane

Table 2
Numerical pain rating scale (NPRS) pain data for all patients' visits, with mean, standard deviation (SD), minimum, and maximum values.

Patient ID	Visit 1	Visit 2	Visit 3	Visit 4	Patient Mean (SD)	Minimum	Maximum
1	3	5	6	7	5.3 (1.7)	3	7
2	7	6	6	6	6.3 (0.5)	6	7
3	6	8	9	9	8.0 (1.4)	6	9
4	5	5	7	7	6.0 (1.2)	5	7
5	0	0	0	0	0.0 (0.0)	0	0
6	5	0	8	7	5.0 (3.6)	0	8
7	3	2	4	*	3.0 (1.0)	2	4
8	5	5	5	5	5.0 (0.0)	5	5
9	10	10	5	10	8.8 (2.5)	5	10
Visit Mean (SD)	4.9 (2.8)	4.6 (3.4)	5.6 (2.6)	6.4 (3.0)	5.3 (2.6)	0	10

* Pain survey data missing.

angular velocity, all demonstrated excellent reliability ranging from 0.93 to 0.96 for all included strides levels (Supplemental Digital Content 1). Supplemental Digital Content 1 also includes individual plots for each axis for each individual patient.

Similar results were seen for discrete gait variables for more affected and less affected sides (Table 3; statistics for left and right side are provided in Supplemental Digital Content 2). Reliability was good-to-excellent, with $ICC_{(2,k)}$ values ranging from 0.89 to 0.98 across all variables and stride inclusion levels, except for frontal plane angular velocity. Despite showing good reliability with increasing number of strides included, the reliability of frontal plane angular velocity was substantially lower on the more affected side ($CMC_{100} = 0.66$) as compared to the less affected side ($CMC_{100} = 0.83$). The means for each visit for all axes are well below all calculated MDCs..

For spatiotemporal variables, stance time, swing time, and stride time had high reliability for both more affected and less affected sides (Table 4; statistics for left and right side are provided in Supplemental Digital Content 2). For these variables, $ICC_{(2,k)}$ ranged from 0.90 to 0.97. While there were limited changes in reliability by increasing stride inclusion levels, the confidence intervals for all variables narrowed. All means for all variables are well below all calculated MDCs.

4. Discussion

The purpose of this study was to evaluate the reliability of wearable sensor data collected across multiple days in out-of-lab settings in a knee OA population. As expected, these findings show that despite variable levels of pain, that the reliability of waveforms, discrete outcome variables, and spatiotemporal variables generally exhibit good-to-excellent reliability. While there is additional work to be done in ensuring wearable sensor reliability for out-of-lab data collections (e.g., free-living collections over several days), the findings from this study suggest that for most axes (i.e., non-frontal plane axes), the underlying waveforms, discrete peak gait variables, and spatiotemporal variables demonstrate at least good reliability over multiple collections in a population of older adults with symptomatic knee osteoarthritis.

It was hypothesized that waveform reliability would remain relatively stable even at higher stride inclusion levels. Our results supported this hypothesis as all acceleration variables were shown to have good-to-excellent reliability for all stride inclusion levels. This finding is similar to other in-lab gait studies with wearable sensors that have reported higher reliability in V and AP acceleration axes and somewhat reduced reliability in the ML acceleration axis (Buckley et al., 2019; Ruder et al., 2022). Frontal plane angular velocity waveforms were shown to have good reliability at higher stride levels, with modest improvements for both more affected and less affected sides. The improved reliability of the frontal plane angular velocity at the highest stride inclusion levels is also promising, as this axis tends to be lower reliability when collected in laboratory settings (Ruder et al., 2022), and given this axis has been used as a proxy for varus thrust, continued improvement of the reliability of this axis is critical for monitoring progression (Chang et al., 2004, 2013; Costello et al., 2020). While this reduced reliability remains a challenge for utilizing this outcome to compare changes following an intervention, future research may look to examine these fluctuations over the course of several days of free-living data to better understand this problem.

Alternatively, it was also hypothesized that the reliability of discrete peaks would improve with more strides included in the analysis. However, discrete peak reliability was shown to be excellent across all stride inclusion levels for all acceleration variables. Interestingly, frontal plane angular velocity peaks only achieved fair reliability in the more affected limb, while good reliability was observed in the less affected limb. This was clearly the most prominent distinction between more and less affected limbs. Further, as previously discussed, while this may speak to its potential clinical utility, it also highlights the challenges in effectively tracking this potentially volatile outcome.

Spatiotemporal variables demonstrated stable, excellent reliability across all variables and stride inclusion levels. The results from spatiotemporal variables are consistent with previous findings from Ader, et al. (Motti Ader et al., 2021), who found that gait variability from spatiotemporal variables from wearable sensors can be established with at least 6 gait cycles. As this study used a minimum of 10 gait cycles, it is not surprising that increasing the number of gait cycles does not considerably improve the already excellent reliability of these measures. However, it should be noted that the Ader et al., assessed over three 30-meter walking assessments, whereas this study was able to see highly reliable gait parameters over a 6-minute walk and over four separate data collections.

While the results of this study were mostly expected, this study was completed outside of a controlled laboratory environment and was conducted in a manner that was semi-controlled level walking. Patients were able to walk on level ground at their own self-selected pace, which in turn allowed for consistent waveforms, peak gait outcomes, and spatiotemporal outcomes. Therefore, it is likely that there were minimal changes even when including up to 100 strides and mostly consistent with similar in-lab studies as well as similar semi-controlled out-of-lab studies (Motti Ader et al., 2021; Storm et al., 2016). As noted in other related gait biomechanics research (e.g. Parkinson's disease, running), how patients move is not captured from in-lab collection and real-world data collection is necessary (Benson et al., 2022; Bouça-Machado et al., 2020). This study represents an initial step to move data collection outside of the in-lab setting, but there remains a need and opportunity for truly free-living assessments outside of the controlled laboratory setting.

This study has several limitations that must be noted. While the motivation of this study was to provide additional evidence for longer, out-of-lab collections, the protocol for each collection was limited to just 6 min of uncontrolled walking. This analysis provides many more strides in comparison to traditional in-lab gait analysis (e.g., 10 strides vs 100 strides), but each collection was completed on a single day and a single walking bout. Within symptomatic osteoarthritis patients, pain may vary drastically day-to-day or even within a day, and a single 6-minute

Table 3
Day-to-day reliability for each side at different step inclusion levels, assessed by coefficient of multiple correlation (for waveforms) and intraclass correlation coefficient (for each discreate variables of interest) between visits 1–4. Mean and standard deviation (SD) were calculated for each day. Coefficient of multiple correlation (CMC) indicate for each axis of interest demonstrates high degree of correlation between signals across all visits while intraclass correlation coefficients (ICC) indicates high degree of correlation between most discrete variable measures. The standard error of the mean (SEM) and minimal detectible change (MDC) was calculated at 95% and 80% confidence intervals for each variable (MDC_{95} and MDC_{80}, respectively). The means for each visit for all axes are less than MDC_{80} and MDC_{95}.

Variable Name	Side	Steps	CMC	ICC	Day 1 Mean (SD)	Day 2 Mean (SD)	Day 3 Mean (SD)	Day 4 Mean (SD)	SEM	MDC_{95}	MDC_{80}
ML Acceleration (m/s^2)	More Affected	10	0.85	0.93 (0.82–0.98)	14.05 (5.91)	14.98 (7.74)	15.63 (7.81)	14.93 (5.98)	1.72	4.76	3.11
		20	0.87	0.94 (0.82–0.98)	14.65 (6.82)	15.34 (7.71)	14.59 (6.62)	14.72 (6.09)	1.66	4.59	3.00
		50	0.89	0.94 (0.82–0.98)	14.47 (6.41)	15.71 (7.40)	14.70 (6.66)	14.53 (5.97)	1.60	4.44	2.91
		100	0.90	0.92 (0.79–0.98)	14.84 (6.25)	15.61 (7.10)	15.03 (6.63)	14.21 (5.56)	1.71	4.74	3.10
	Less Affected	10	0.83	0.95 (0.84–0.99)	16.89 (10.46)	16.37 (9.43)	12.21 (6.19)	14.12 (7.61)	1.96	5.43	3.55
		20	0.84	0.95 (0.85–0.99)	16.94 (10.11)	16.56 (10.06)	12.22 (6.04)	14.01 (7.45)	1.92	5.33	3.48
		50	0.85	0.96 (0.87–0.99)	16.63 (9.52)	16.45 (9.55)	12.08 (6.13)	14.24 (7.73)	1.69	4.68	3.06
		100	0.87	0.95 (0.86–0.99)	16.71 (9.39)	16.22 (9.20)	12.07 (5.98)	14.24 (7.32)	1.70	4.72	3.09
V Acceleration (m/s^2)	More Affected	10	0.95	0.95 (0.86–0.99)	29.00 (6.36)	29.78 (10.47)	30.05 (13.10)	27.62 (8.14)	2.17	6.02	3.94
		20	0.95	0.94 (0.84–0.99)	29.75 (7.17)	30.15 (10.61)	30.10 (13.33)	28.09 (8.32)	2.34	6.48	4.24
		50	0.95	0.94 (0.83–0.98)	29.36 (6.66)	30.70 (11.14)	29.88 (13.74)	28.01 (8.13)	2.50	6.92	4.52
		100	0.95	0.94 (0.84–0.98)	29.42 (6.81)	30.36 (10.58)	29.96 (13.93)	27.72 (7.60)	2.39	6.62	4.33
	Less Affected	10	0.94	0.96 (0.89–0.99)	30.58 (10.81)	29.07 (12.11)	31.28 (15.96)	30.34 (16.65)	2.72	7.53	4.93
		20	0.94	0.96 (0.90–0.99)	31.31 (10.62)	29.73 (12.50)	31.24 (15.88)	30.53 (16.87)	2.58	7.15	4.67
		50	0.94	0.97 (0.91–0.99)	31.14 (10.91)	30.06 (12.35)	31.32 (16.17)	31.12 (17.39)	2.46	6.81	4.45
		100	0.95	0.98 (0.93–0.99)	31.22 (11.41)	30.24 (12.21)	31.29 (15.83)	30.86 (16.66)	2.13	5.90	3.86
AP Acceleration (m/s^2)	More Affected	10	0.94	0.90 (0.73–0.97)	13.27 (4.28)	12.14 (5.35)	11.76 (6.26)	11.53 (4.86)	1.60	4.43	2.90
		20	0.94	0.89 (0.71–0.97)	13.62 (4.48)	12.31 (5.55)	11.74 (6.57)	11.87 (5.45)	1.75	4.85	3.17
		50	0.95	0.89 (0.71–0.97)	13.34 (4.71)	12.39 (5.49)	11.58 (6.99)	11.68 (5.00)	1.76	4.88	3.19
		100	0.95	0.90 (0.73–0.97)	13.43 (4.59)	12.14 (5.35)	11.43 (6.95)	11.55 (4.85)	1.68	4.66	3.05
	Less Affected	10	0.94	0.93 (0.82–0.98)	13.56 (5.53)	12.36 (5.53)	12.63 (5.23)	11.19 (7.01)	1.45	4.02	2.63
		20	0.94	0.93 (0.82–0.98)	13.77 (5.42)	12.52 (5.55)	12.68 (5.51)	11.52 (7.03)	1.48	4.10	2.68
		50	0.95	0.95 (0.86–0.99)	13.74 (5.48)	12.77 (5.91)	12.51 (5.86)	11.36 (6.26)	1.27	3.53	2.31
		100	0.96	0.95 (0.87–0.99)	13.44 (5.64)	12.84 (5.98)	12.65 (6.23)	11.03 (6.14)	1.26	3.48	2.28
R Acceleration (m/s^2)	More Affected	10	0.94	0.97 (0.91–0.99)	35.35 (9.28)	34.49 (13.74)	34.07 (14.48)	33.36 (11.11)	2.09	5.78	3.78
		20	0.95	0.96 (0.88–0.99)	36.23 (9.42)	35.23 (14.06)	34.41 (14.91)	33.49 (11.05)	2.47	6.85	4.48
		50	0.96	0.96 (0.90–0.99)	35.83 (9.05)	35.98 (14.48)	34.52 (15.49)	34.09 (11.60)	2.35	6.52	4.26
		100	0.96	0.96 (0.90–0.99)	36.09 (9.04)	35.84 (13.89)	34.71 (15.76)	33.68 (11.55)	2.31	6.40	4.19
	Less Affected	10	0.93	0.97 (0.92–0.99)	37.85 (14.57)	36.65 (15.09)	36.46 (17.34)	37.04 (19.15)	2.69	7.46	4.88
		20	0.93	0.97 (0.93–0.99)	38.48 (13.77)	37.25 (15.48)	36.17 (17.36)	37.15 (19.68)	2.58	7.15	4.67
		50	0.94	0.98 (0.94–0.99)	38.43 (14.09)	37.30 (15.21)	36.62 (17.40)	37.76 (19.83)	2.42	6.72	4.39
		100	0.94	0.98 (0.95–1.00)	38.59 (14.38)	37.30 (14.89)	36.69 (17.69)	37.36 (18.95)	2.22	6.15	4.02
Frontal Plane Angular Velocity (degrees/second)	More Affected	10	0.74	0.61 (-0.05–0.90)	83.84 (43.94)	67.14 (20.36)	66.47 (26.53)	85.95 (50.31)	22.97	63.67	41.63
		20	0.77	0.63 (0.00–0.90)	89.18 (39.44)	68.15 (21.87)	67.40 (27.38)	87.72 (54.33)	23.07	63.96	41.82
		50	0.77	0.67 (0.13–0.92)	87.11 (35.99)	65.29 (18.83)	67.50 (29.22)	85.41 (55.50)	21.27	58.96	38.55
		100	0.81	0.66 (0.09–0.91)	84.45 (34.41)	66.27 (16.51)	66.67 (27.92)	82.82 (51.92)	20.13	55.79	36.48
	Less Affected	10	0.73	0.81 (0.47–0.95)	81.98 (46.37)	65.63 (25.10)	81.25 (36.15)	84.66 (69.28)	20.02	55.48	36.28
		20	0.76	0.84 (0.57–0.96)	86.54 (43.25)	68.13 (29.88)	74.47 (39.77)	86.01 (70.23)	18.45	51.14	33.44
		50	0.78	0.84 (0.56–0.96)	82.46 (35.87)	63.35 (27.22)	73.75 (38.44)	85.34 (67.76)	17.75	49.20	32.17
		100	0.79	0.83 (0.53–0.96)	79.75 (36.95)	58.15 (25.09)	75.25 (38.74)	83.17 (64.91)	17.97	49.80	32.56

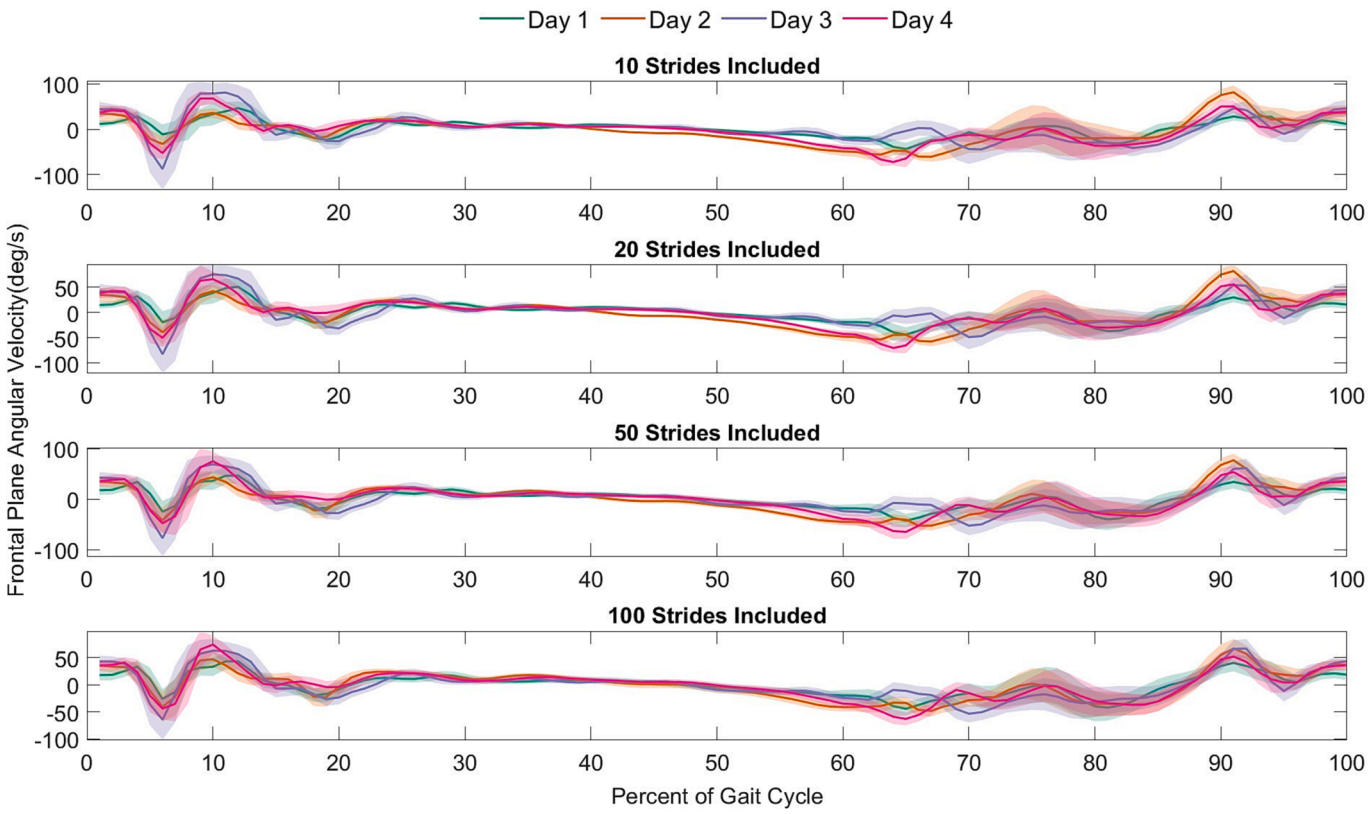

Fig. 2. Representative ensemble curve for frontal plane angular velocity showing narrowing of confidence intervals when using 10, 20, 50 and 100 strides. Each line is the mean from a data collection day, with shading representing the standard deviation (Day 1 - green, Day 2 - orange, Day 3 - purple, Day 4 - fushia). Full plots for each axis at each stride inclusion level are shown in Supplemental Digital Content 1. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 4
Day-to-day reliability spatiotemporal parameters for each side at different step inclusion levels, assessed by intraclass correlation coefficient visits 1–4. Intraclass correlation coefficients (ICC) indicates high degree of correlation between for all spatiotemporal variables. Mean and standard deviation (SD) were calculated for each day. The standard error of the mean (SEM) and minimal detectible change was calculated at 95% and 80% confidence intervals for each variable (MDC_{95} and MDC_{80}, respectively). The means for each visit for all parameters are less than MDC_{80} and MDC_{95}.

Variable Name	Side	Steps	ICC	Day 1 Mean (SD)	Day 2 Mean (SD)	Day 3 Mean (SD)	Day 4 Mean (SD)	SEM	MDC_{95}	MDC_{80}
Stance Time (seconds)	More Affected	10	0.95 (0.87–0.99)	0.64 (0.06)	0.66 (0.09)	0.64 (0.08)	0.65 (0.05)	0.02	0.06	0.04
		20	0.96 (0.9–0.99)	0.64 (0.06)	0.66 (0.09)	0.64 (0.08)	0.65 (0.05)	0.02	0.06	0.04
		50	0.97 (0.91–0.99)	0.65 (0.06)	0.66 (0.09)	0.65 (0.08)	0.65 (0.05)	0.02	0.05	0.03
		100	0.97 (0.91–0.99)	0.65 (0.06)	0.66 (0.09)	0.65 (0.08)	0.66 (0.05)	0.02	0.05	0.03
	Less Affected	10	0.93 (0.81–0.98)	0.65 (0.05)	0.68 (0.08)	0.64 (0.07)	0.67 (0.06)	0.02	0.06	0.04
		20	0.93 (0.82–0.98)	0.65 (0.05)	0.68 (0.08)	0.65 (0.07)	0.66 (0.06)	0.02	0.05	0.04
		50	0.96 (0.89–0.99)	0.66 (0.05)	0.67 (0.07)	0.65 (0.07)	0.66 (0.06)	0.02	0.05	0.03
		100	0.97 (0.91–0.99)	0.66 (0.05)	0.68 (0.07)	0.66 (0.07)	0.67 (0.06)	0.02	0.05	0.03
Swing Time (seconds)	More Affected	10	0.90 (0.72–0.97)	0.47 (0.02)	0.48 (0.03)	0.47 (0.02)	0.48 (0.03)	0.01	0.04	0.03
		20	0.92 (0.77–0.98)	0.47 (0.02)	0.47 (0.04)	0.47 (0.03)	0.48 (0.03)	0.01	0.04	0.02
		50	0.94 (0.83–0.98)	0.47 (0.02)	0.47 (0.04)	0.47 (0.03)	0.48 (0.03)	0.01	0.03	0.02
		100	0.94 (0.84–0.99)	0.47 (0.02)	0.47 (0.04)	0.47 (0.03)	0.48 (0.03)	0.01	0.03	0.02
	Less Affected	10	0.93 (0.81–0.98)	0.46 (0.02)	0.46 (0.05)	0.46 (0.03)	0.46 (0.03)	0.02	0.05	0.03
		20	0.94 (0.84–0.99)	0.46 (0.03)	0.46 (0.05)	0.47 (0.03)	0.46 (0.03)	0.02	0.05	0.03
		50	0.94 (0.84–0.99)	0.46 (0.03)	0.46 (0.05)	0.47 (0.03)	0.46 (0.03)	0.01	0.04	0.02
		100	0.94 (0.83–0.98)	0.46 (0.03)	0.46 (0.05)	0.47 (0.03)	0.46 (0.03)	0.01	0.03	0.02
Stride Time (seconds)	More Affected	10	0.94 (0.85–0.99)	1.11 (0.07)	1.14 (0.13)	1.11 (0.09)	1.13 (0.07)	0.01	0.02	0.02
		20	0.95 (0.87–0.99)	1.11 (0.08)	1.14 (0.13)	1.11 (0.09)	1.13 (0.07)	0.01	0.02	0.02
		50	0.97 (0.91–0.99)	1.12 (0.08)	1.13 (0.12)	1.12 (0.10)	1.13 (0.07)	0.01	0.02	0.01
		100	0.97 (0.91–0.99)	1.12 (0.07)	1.14 (0.12)	1.12 (0.10)	1.13 (0.07)	0.01	0.02	0.01
	Less Affected	10	0.94 (0.85–0.99)	1.11 (0.07)	1.14 (0.12)	1.11 (0.10)	1.13 (0.07)	0.01	0.02	0.02
		20	0.95 (0.88–0.99)	1.11 (0.08)	1.14 (0.12)	1.11 (0.09)	1.13 (0.07)	0.01	0.02	0.01
		50	0.97 (0.91–0.99)	1.12 (0.08)	1.13 (0.12)	1.12 (0.10)	1.13 (0.07)	0.01	0.02	0.01
		100	0.97 (0.91–0.99)	1.12 (0.08)	1.14 (0.12)	1.12 (0.10)	1.13 (0.07)	0.01	0.02	0.02
Cadence (steps/minute)		10	0.95 (0.87–0.99)	108.32 (7.03)	106.57 (10.97)	109.17 (9.53)	106.52 (6.72)	1.83	5.07	3.31
		20	0.96 (0.89–0.99)	108.32 (7.31)	106.69 (10.89)	108.73 (9.47)	106.82 (7.18)	1.69	4.69	3.06
		50	0.97 (0.92–0.99)	108.00 (7.38)	107.15 (10.80)	108.16 (9.80)	106.94 (6.68)	1.45	4.02	2.63
		100	0.97 (0.92–0.99)	107.74 (7.21)	106.46 (10.49)	107.50 (9.79)	106.24 (6.75)	1.43	3.97	2.60

walking bout cannot capture potential changes in gait due to these fluctuations. It is critical that future studies further examine changes in biomechanics, including accelerations and angular velocities, out-of-lab over longer periods of time to account for these fluctuations. In addition to the short collection duration, the lower sample size of the study population likely does not fully capture the full range of accelerations and angular velocities in outside-of-lab osteoarthritic gait, and these results may not reflect the full range of patients experiencing pain related to knee osteoarthritis. While the limited sample size, lowered by COVID-19 restrictions at the time of research, caused us to miss additional patients, based on our results, the greatest impact would have likely narrowed the width of the confidence intervals. Nevertheless, this study showed the potential reliability across multiple days in a clinical population, and future studies examining outside-of-lab gait are encouraged to collect larger sample sizes to reflect this reality.

In summary, this study provides evidence for the reliability of sensors in a symptomatic knee osteoarthritis population as well as additional use within clinical settings for monitoring disease progression. This study demonstrated that wearable sensors have good-to-excellent reliability across a wide range of strides over multiple days outside of the traditional laboratory environment. The results support additional and increased data collection outside of the lab to more accurately quantify the biomechanics of clinical populations that has pain fluctuations that may affect gait that would otherwise not be captured in shorter in-lab collections.

CRediT authorship contribution statement

Matthew C. Ruder: Conceptualization, Funding acquisition, Writing – original draft, Writing – review & editing, Visualization, Investigation, Validation, Formal analysis. **Zaryan Masood:** Conceptualization, Data curation, Writing – review & editing, Investigation, Methodology. **Dylan Kobsar:** Writing – review & editing, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, 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.

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Appendix A. Supplementary data

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