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Research article

Multivariable model for gait pattern differentiation in elderly patients with hip and knee osteoarthritis: A wearable sensor approach

Arash Ghaffari [a,*], Pernille Damborg Clasen [a], Rikke Vindberg Boel [a], Andreas Kappel [a], Thomas Jakobsen [a], John Rasmussen [b], Søren Kold [a], Ole Rahbek [a]

[a] *Interdisciplinary Orthopaedics, Aalborg University Hospital, Aalborg, Denmark*
[b] *Department of Materials and Production, Aalborg University, Aalborg East, Denmark*

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ABSTRACT

Background: Hip and knee osteoarthritis (OA) patients demonstrate distinct gait patterns, yet detecting subtle abnormalities with wearable sensors remains uncertain. This study aimed to assess a predictive model's efficacy in distinguishing between hip and knee OA gait patterns using accelerometer data.
Method: Participants with hip or knee OA underwent overground walking assessments, recording lower limb accelerations for subsequent time and frequency domain analyses. Logistic regression with regularization identified associations between frequency domain features of acceleration signals and OA, and k-nearest neighbor classification distinguished knee and hip OA based on selected acceleration signal features.
Findings: We included 57 knee OA patients (30 females, median age 68 [range 49–89], median BMI 29.7 [range 21.0–45.9]) and 42 hip OA patients (19 females, median age 70 [range 47–89], median BMI 28.3 [range 20.4–37.2]). No significant difference could be found in the time domain's averaged shape of acceleration signals. However, in the frequency domain, five selected features showed a diagnostic ability to differentiate between knee and hip OA. Using these features, a model achieved a 77 % accuracy in classifying gait cycles into hip or knee OA groups, with average precision, recall, and F1 score of 77 %, 76 %, and 78 %, respectively.
Interpretation: The study demonstrates the effectiveness of wearable sensors in differentiating gait patterns between individuals with hip and knee OA, specifically in the frequency domain. The results highlights the promising potential of wearable sensors and advanced signal processing techniques for objective assessment of OA in clinical settings.

1. Introduction

Osteoarthritis is a prevalent chronic joint disease expected to increase due to aging populations [1]. Primary hip and knee OA are frequently observed in elderly individuals, limiting their mobility and reducing their quality of life [2]. Older people often exhibit concurrent primary hip and knee OA, with age as a prominent risk factor [3]. However, identifying the dominant problem is crucial for

* Corresponding author. Interdisciplinary Orthopaedics, Aalborg University Hospital, Hobrovej 18 -22, 9000, Aalborg, Denmark.
E-mail address: a.ghaffari@rn.dk (A. Ghaffari).

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adequate care, as one may significantly impact the patient's function and movement. Some studies have demonstrated biomechanical discrepancies between the gait of hip and knee OA patients [4–6]. While comprehensive gait analysis necessitated specialized labs, many clinicians trust their judgment to identify abnormalities through mere observation. However, exclusive reliance on observational deductions might compromise reliability and practicality.

Wearable sensors have revolutionized gait analysis, offering a convenient, accessible, and cost-effective approach for patients and clinicians [7]. Beyond their economic appeal and accessibility, wearable sensors grant clinicians a broader data spectrum, encompassing everyday activity metrics and sleep patterns, critical for informed clinical decisions [8]. The elegance of single-sensor systems lies in their user-friendliness, which could translate to better patient adherence for sustained monitoring. Nevertheless, as wearable technology attains increasing popularity in human movement assessment, its capabilities in detailed gait analysis, especially outside lab confines, warrant further probing. While existing studies indicate that these devices can reliably identify abnormal walking patterns [9], questions still arise about their ability to detect minor gait irregularities, for instance, when differentiating between individuals with hip and knee OA. This concern is heightened with sensors intended for prolonged use, as they frequently offer a reduced data quality, resulting from lower sampling rates and measurements taken outside controlled environments.

This study aims to evaluate the capability of wearable sensors designed for daily use to differentiate between the gait patterns of individuals affected by hip and knee OA. We used advanced signal processing and machine learning techniques to extract and interpret relevant kinematic data from these sensors. Given the inherent variability in OA presentations, we evaluated the efficacy and limitations of single-sensor analysis in distinguishing these specific OA manifestations.

2. Method

This article complies with the Transparent Reporting of a multivariable prediction model for Individual Prognosis or Diagnosis (TRIPOD) guidelines [10].

2.1. Participants

The study was prospectively conducted at Aalborg University Hospital in Denmark from February to April 2023. Patients with knee or hip OA were diagnosed by orthopedic surgeons prior to recruitment. Eligible patients were assessed at the clinic and included after obtaining informed consent. We intentionally selected a broad spectrum of OA patients, including those with contralateral TKA or THA, to enhance the generalizability of our findings and reflect various real-world clinical scenarios. Nonetheless, we excluded patients with lower limb surgeries within the last six months, individuals with severe pain beyond the knee and hip joints, those with knee and hip issues unrelated to OA, individuals with neurological movement disorders, and those with inflammatory arthritis to ensure that the study specifically targeted the effects of OA on gait patterns, minimizing confounding factors that could skew the results.

The primary outcome variable was the predominant presence of hip or knee OA causing walking difficulties, which was determined through a combined objective and subjective assessment of pain and problems in the hip and knee joints. Any discrepancy between patients' self-reports and orthopedic evaluations led to exclusion from the study.

2.2. Wearable sensors

We employed the SENS wearable sensors (SENS Motion®, Copenhagen, Denmark) for this study. These small devices (50 × 21 × 5 mm, weighing 8 g) incorporate a triaxial accelerometer that samples at 12.5 Hz within a range of ±4G. The sensors are specifically designed for long-term patient activity monitoring, boasting a battery life of almost 16 weeks. Prior research has validated the reliability and precision of these sensors [11,12]. Notably, while 12.5 Hz might be perceived as a modest sampling rate for gait accelerometry, previous studies affirm its capacity to yield significant insights into OA patients' gait [9].

2.3. Data collection

Demographic Information: We recorded participants' age, sex, height, and weight.

Pain Evaluation: The average pain in the hip and knee joints over the last week was assessed using an 11-point numeric rating scale (NRS) with values from 0 to 10.

Questionnaires: We assessed knee and hip OA-related issues with the knee injury and osteoarthritis outcome score (KOOS) [13] and hip disability and osteoarthritis outcome score (HOOS) [14], respectively. The KOOS/HOOS scores were analyzed across five dimensions: pain, other symptoms, daily activity limitations, restrictions in sports and recreational activities, and quality of life (QoL).

Limb Selection: For patients with bilateral hip/knee OA, we selected the limb with greater pain for analysis. If both limbs had equal pain and problems, one side was randomly chosen for sensor attachement.

Limb Length Discrepancies (LLD): Considering the potential of LLD to influence gait patterns, we measured this by subtracting the contralateral limb length from the studied limb length. Using a tape measure, a sole examiner determined the distance from the anterior superior iliac spine (ASIS) to the medial malleolus [15].

Severity Assessment via Radiographs: Existing radiographs were used to evaluate the severity of knee or hip OA. We employed the Kellgren-Lawrence classification [16] for knee OA severity and the Tönnis classification [17] for hip OA. Additionally, for knee OA patients, we ascertained the knee joint's alignment (varus, valgus, or neutral) through the femorotibial angle, observed on non-weight bearing short knee radiographs in the anteroposterior projection [18].

Gait Analysis: We affixed sensors to the participants' lower limbs using adhesive patches. The sensors were positioned on the lateral aspect of the distal thigh, following manufacturer guidelines, and recorded acceleration signals during about 5-min walking intervals. Participants walked at their natural pace on straight pathways within the hospital. The sensors captured acceleration in the craniocaudal (CC), anteroposterior (AP), and mediolateral (ML) directions.

2.4. Signal processing

Sensor Data Analysis: Our focus was on data from the sensor ipsilateral with the affected joint. In cases of bilateral joint involvement, the limb with greater pain was selected for analysis, or if pain was equal, a random selection was made. The 3D signals of the walking period on the CC, AP, and ML axes were extracted and resampled by a factor of 5.

Signal Filtering: A 4th-order Butterworth low-pass filter with a cutoff frequency of 4 Hz was used to eliminate noise from soft tissue vibrations. Choosing 4 Hz as the cutoff frequency for filtering the acceleration signals was based on analyzing the difference between filtered and unfiltered signals performed over a wide range of cutoff frequencies. This frequency determined to be optimal for minimizing noise while retaining the essential characteristics of the gait signals.

Walking Bouts Identification: Walking bouts were defined as continuous walking periods without interruptions. The walking pathways in our study were designed as long back-and-forth straight routes. Any accelerations corresponding to changes in direction were distinctly evident in the data based on the characteristic shapes of the acceleration patterns. These apparent deviations were recognized during the data processing phase and were excluded from the analysis to ensure the consistency of the acceleration data under study. We selected five consecutive strides for each individual, specifically from the central section of each walking bout, ensuring that every subject had an equivalent number of gait cycles included for analysis. These strides were then segmented into five successive, non-overlapping windows, each representing a unique gait cycle. For cohesive comparison and analysis, gait cycles were standardized and divided into 101 points, from 0 to 100.

Gait Event Detection: Foot-contact and foot-off events were identified using the methodology proposed by Gurchiek et al. [19].

Harmonic Analysis: We calculated the angular frequency (ω) for every stride and utilized the fast Fourier transform (FFT) to assess the power for the initial five harmonics across the CC, AP, and ML signal axes. Power values were determined by summing the squares of the sine and cosine coefficients for each harmonic [20].

2.5. Comparison of time-domain waveforms

We compared lower limb accelerations of hip and knee OA patients using statistical parametric mapping (SPM) method [21]. Before conducting the SPM analysis, the gait cycles were averaged across each subject. Python's spm1d code (v.M0.1, www.spm1d.org) was utilized to execute the SPM analyses on averaged accelerations throughout a single gait cycle employing a two-tailed paired *t*-test. A significance level of $\alpha = 0.05$ was used to determine statistical significance. The critical threshold was computed to detect supra-threshold clusters.

2.6. Comparison of frequency-domain spectra

2.6.1. Train-test-split

To ensure an unbiased model evaluation and to prevent overfitting, we divided our data into training and test sets, maintaining a ratio of 75 % for training and 25 % for testing. Only the training data was used during the feature selection and model training phases, and the test data was kept untouched until the final evaluation phase. This approach prevented any inadvertent "peeking" at the test data and ensured that our results would likely generalize well to new, unseen data.

2.6.2. Mixed effect logistic regression model

We employed generalized mixed-effect modeling for binary data to investigate the association between the power of acceleration signal harmonics and hip or knee OA while considering the clustering of multiple waveforms obtained from the same participants. The outcome variable was the presence of hip vs. knee OA. Different patients were utilized as random intercepts in the model. The predictor variables included the power at each initial five harmonics of acceleration signals along the CC, AP, and ML axes (15 variables), as well as the stride angular frequency (ω) in Radian/s, the participant's age in years and BMI in kg/m2, as continuous variables, in addition to participants' sex, as a categorical variable. Before model fitting, the continuous variables were scaled by adjusting their means to zero and standard deviations to one.

We used L1-regularization or least absolute shrinkage and selection operator (LASSO) [22] with glmmLasso in R to prevent overfitting and identify optimal independent variables. We employed a range of penalty values, lambda, from 10^{-4} to 10^{10} to identify the optimal value that yielded the highest accuracy for generalized linear mixed models using an L1-penalized estimation model. The selection of lambda was based on the criterion of λ_{1se}, which represents the largest lambda value within one standard error of the minimum binomial deviance. As mentioned earlier, feature selection was only done on training data to prevent data leakage. Bootstrapping was used to estimate 95 % confidence intervals via 1000 iterations.

2.6.3. K-NN classification

We employed features identified by the mixed-effect model from the training dataset to classify acceleration signals of individual strides, distinguishing between patients with either hip or knee OA. A grid search was conducted to optimize the hyperparameters of the K-NN classifier and improve its overall performance.

Finally, we used the test dataset to evaluate the k-NN model's accuracy and performed bootstrapping with 1000 iterations to estimate confidence intervals. Accuracy, precision, recall, and F1 score [23] were measured to assess the model's performance.

2.7. Statistical analysis

Patient characteristics in the knee and hip OA groups were summarized using descriptive statistics. Numerical variables were presented using median and range, while categorical variables were shown as counts and percentages. Mann-Whitney and Fisher Exact tests were used to compare groups. A convenient sample size was chosen for this exploratory study to evaluate the feasibility and preliminary effectiveness of the method.

3. Results

3.1. Participants

Fig. 1 presents the participant flow chart. Two patients were excluded from the study due to missing sensor data, and only cases with complete data were included in the analysis.

Characteristics of the participants are presented in Table 1.

3.2. Comparison of time-domain waveforms

SPM analysis could not reveal significant differences exceeding the critical thresholds in acceleration patterns between individuals with hip and knee OA along the CC, AP, and ML axes throughout the gait cycle (Fig. 2).

3.3. Comparison of frequency-domain spectra

The optimal penalty value (λ_{1se}) for the generalized linear mixed effect model with LASSO was 70. Table 2 provides the model's coefficients with lambda equal to 70, demonstrating the contributions of the selected variables to the model's predictive power.

The features selected by the generalized linear mixed effect model with LASSO, excluding BMI (only signal features were selected), were utilized for the K-NN classification model. After conducting grid search cross-validation, we identified the optimal configuration for the K-NN model as $K = 6$, using the "auto" algorithm, "Minkowski" metric, and uniform weights. The model achieved an overall accuracy of 77 % for classifying gait cycles into hip or knee OA groups.

The performance metrics of the model are presented in Table 3. The parallel coordinate plot in Fig. 3 provides a visual comparison and intuitive representation of the distribution of the features used in the k-NN model in both groups.

Fig. 4 presents a three-dimensional distribution plot of the participants for three features with the most considerable coefficients in the generalized linear mixed effect model with LASSO.

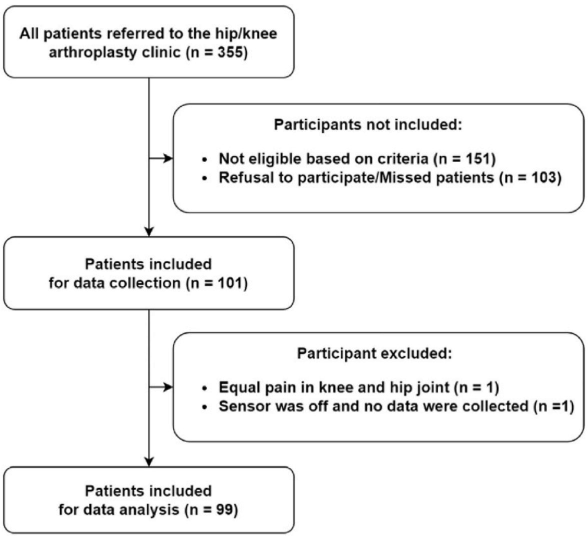


Fig. 1. – Participants flow chart.

Table 1
– Characteristics of the participants.

Variable			Knee OA (n=57)	Hip OA (n=42)	Total (n=99)	p-value
Age (years) (median [Range])			68 [49–89]	70 [47–89]	69 [47–89]	0.2
Sex	Female (n (%))		30 (53)	19 (45)	49 (49)	0.5
	Male (n (%))		27 (47)	23 (55)	50 (51)	
Weight (kg) (median [Range])			90 [53–125]	82 [52–115]	88 [52–125]	0.07
Height (cm) (median [Range])			172 [148–197]	173 [153–187]	172 [148–197]	0.9
BMI (kg/m[b]) (median [Range])			29.7 [21.0–45.9]	28.3 [20.4–37.2]	28.7 [20.4–45.9]	0.04
KOOS/HOOS[a] (median [IQR[b]])	Pain		58.3 [41.7–70.8]	55.0 [45.0–69.4]	57.5 [44.4–70.0]	0.9
	Symptom		60.7 [42.9–82.1]	50.0 [41.3–58.8]	53.6 [42.9–70.0]	0.01
	ADL		73.5 [58.8–84.6]	66.2 [57.7–81.3]	70.6 [58.8–83.8]	0.5
	Sport		15.0 [2.5–32.5]	31.3 [20.3–54.7]	25.0 [5.0–40.0]	<0.001
	QoL		37.5 [25.0–56.3]	40.6 [25.0–56.3]	37.5 [25.0–56.3]	0.98
Studied limb	Side	Right (n (%))	27 (47)	20 (48)	47 (47)	0.09
		Left (n (%))	17 (30)	19 (45)	36 (36)	
		Both (n (%))	13 (23)	3 (7)	16 (16)	
	LLD[c] (cm) (median [IQR])		0 [-1 – 1]	0 [-1 – 1]	0 [-1 – 1]	0.2
	Knee pain NRS[d] (median [IQR])		6 [5–8]	0 [0–3]	5 [0–7]	<0.001
	Hip pain NRS (median [IQR])		0 [0-0]	6 [5–7]	2 [0–6]	<0.001
	Knee OA[e] grade (n (%))	0	0	–	–	–
		1	9 (16)	–	–	–
		2	17 (30)	–	–	–
		3	21 (37)	–	–	–
		4	10 (18)	–	–	–
	Hip OA grade (n (%))	0	–	0	–	–
		1	–	12 (29)	–	–
		2	–	19 (46)	–	–
		3	–	10 (24)	–	–
	Knee alignment (n (%))	Neutral	29 (51)	–	–	–
		Varus	19 (33)	–	–	–
		Valgus	9 (16)	–	–	–
Contralateral limb	Knee pain NRS (median [IQR])		0 [0–4]	0 [0-0]	0 [0–3]	0.003
	Hip pain NRS (median [IQR])		0 [0-0]	0 [0–3]	0 [0–1]	0.2
	Knee OA grade (n (%))	0	1 (2)	–	–	–
		1	16 (28)	–	–	–
		2	18 (32)	–	–	–
		3	10 (18)	–	–	–
		4	5 (9)	–	–	–
		TKA	5 (9)	–	–	–
	Hip OA grade (n (%))	0	–	5 (12)	–	–
		1	–	17 (41)	–	–
		2	–	7 (17)	–	–
		3	–	0	–	–
		THA	–	12 (29)	–	–
	Knee alignment (n (%))	Neutral	38 (67)	–	–	–
		Varus	13 (23)	–	–	–
		Valgus	4 (7)	–	–	–
		Unknown	2 (4)	–	–	–

[a] Knee osteoarthritis and injury outcome score and hip disability and osteoarthritis outcome score, including five subscales: pain, symptoms, limitations in activities of daily living (ADL), restrictions in sports and recreational activities, and quality of life (QoL).
[b] Interquartile range.
[c] Lower limb discrepancy.
[d] Numerical rating scale.
[e] Osteoarthritis.

4. Discussion

We evaluated the capability of wearable sensors designed for physical activity monitoring in differentiating the gait patterns of individuals with hip and knee OA. By analyzing the harmonics of acceleration signals, we achieved a 77 % accuracy rate in distinguishing between the two OA types.

Individuals with knee and hip OA exhibit different walking patterns, potentially due to differences in joint anatomy, biomechanics, and muscle activation patterns [6]. Research has shown that patients with hip OA have lower hip joint moments in both the frontal and sagittal planes than controls [24], whereas those with knee OA have higher knee joint moments in the frontal plane than controls [25]. These differences may reflect adaptive strategies to alleviate pain and frontal plane malalignment in each condition [26]. Few studies have directly compared gait biomechanics in individuals with hip and knee OA. In a recent survey by Nüesch et al. SPM analysis on inertial sensor data revealed that patients with knee OA, in comparison to patients with hip OA, exhibited less knee flexion during midstance, terminal stance, and pre-swing, as well as less hip extension during late swing and initial contact [27]. In contrast, Schmitt

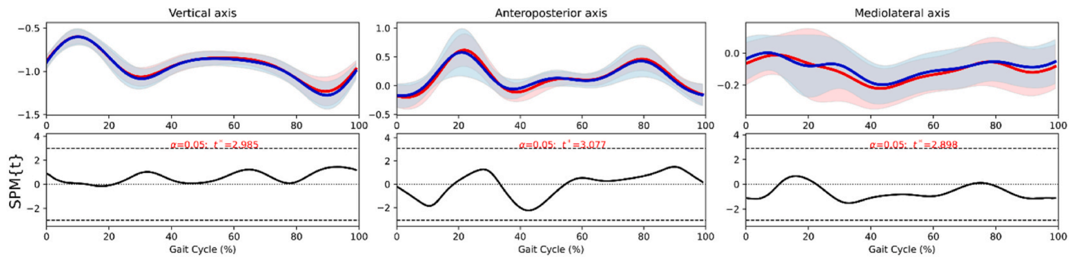


Fig. 2. – Statistical parametric mapping (SPM) analysis of acceleration patterns along the craniocaudal (CC), anteroposterior (AP), and mediolateral (ML) axes in patients with hip and knee osteoarthritis (OA). The upper panel shows the mean trajectories of linear accelerations in patients with knee OA (blue) and hip OA (red). The lower panel displays the two-sample *t*-test statistic SPM {t}. The black dashed line indicates the critical threshold value (t*) at α = 0.05. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Table 2
The estimated coefficients in the generalized linear mixed effect model with L1-regularization at penalty term (lambda) equal to 70.

Coefficients		Estimate	95 % Confidence interval
Craniocaudal (CC) axis	Power 1st harmonic	−0.58	[-0.96, −0.48]
	Power 2nd harmonic	−0.51	[-0.79, −0.32]
	Power 3rd harmonic	–	–
	Power 4th harmonic	–	–
	Power 5th harmonic	–	–
Anteroposterior (AP) axis	Power 1st harmonic	–	–
	Power 2nd harmonic	–	–
	Power 3rd harmonic	–	–
	Power 4th harmonic	0.50	[0.13, 0.87]
	Power 5th harmonic	–	–
Mediolateral (ML) axis	Power 1st harmonic	–	–
	Power 2nd harmonic	0.53	[0.14, 0.71]
	Power 3rd harmonic	–	–
	Power 4th harmonic	−0.40	[-0.64, −0.04]
	Power 5th harmonic	–	–
Stride angular frequency (ω) (Radian/s)		–	–
Age (yrs)		–	–
Sex (Male)		–	–
BMI (kg/m^2)		−1.2	[-1.4, −1.0]

Table 3
– The performance metrics of the classification model.

Performance metric	Group	
	Knee OA	Hip OA
Percision	79 [75, 84]	75 [70, 81]
Recall	81 [75, 87]	72 [65, 81]
F1-Score	80 [77, 83]	74 [69, 78]
Accuracy	77 [74, 81]	

et al. utilized a motion capture gait analysis system and found that individuals with knee OA displayed greater knee flexion during the stance phase [28]. The present study relies on a single sensor, which measures point accelerations but does not directly measure relationships between segments and is therefore blind to differences in joint angles, except as their indirect effects on the point accelerations.

In this study, SPM analysis did not reveal significant differences in the shape of acceleration signal waveforms between patients with knee and hip OA. It is possible that the stride-to-stride variations within each patient [29–32], as well as the individual variations within each group [33–35], overshadowed the differences in waveform shape at the highest level, making it challenging to detect distinctions based solely on averaged data. By utilizing logistic mixed effect modeling in the analysis, a comprehensive approach was adopted that accounted for individual variations and captured heterogeneity within the data, while also considering factors such as age, sex, and BMI that can impact the gait pattern [36].

Time-domain analysis is a valuable approach for examining variations and patterns in waveforms over time, providing insights into the temporal characteristics of gait [37]. On the other hand, frequency-domain analysis identifies frequency contents and patterns related to gait by decomposing the signal into its constituent frequency components [38]. Incorporating signal harmonics and averaged

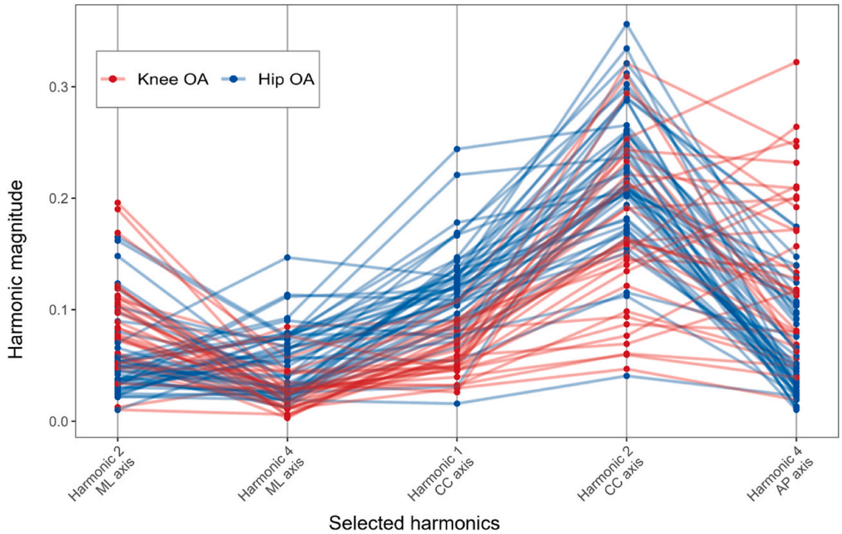
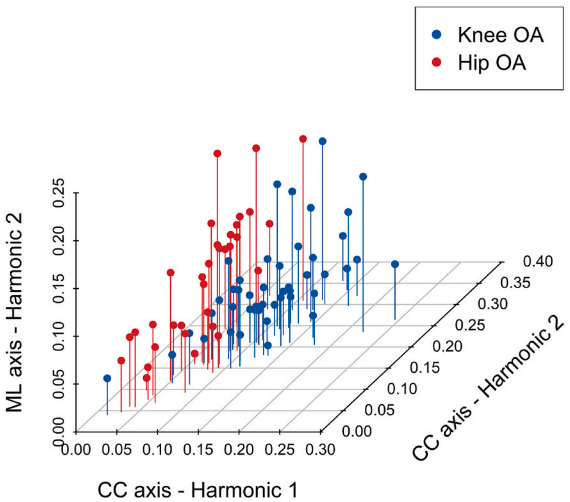


Fig. 3. – Parallel plot demonstrating the distribution of the selected features between participants with hip and knee OA.



Figs. 4. 3D scatterplot demonstrating the clusters of participants with hip and knee OA based on three features.

waveform analysis enhances the discriminatory power and offers a more comprehensive data assessment. This approach enables the identification of subtle variations and specific features that can effectively differentiate between different groups or conditions.

In this study, we have employed LASSO logistic regression as a feature selection method, which offers several advantages in this specific context. LASSO regression effectively addresses issues such as multicollinearity and overfitting by automatically selecting the most relevant predictors for the outcome variable, resulting in a more concise model representation [39]. This technique has garnered attention in gait analysis research [9]. By utilizing a subset of predictors instead of all features, we can address the challenges of high-dimensional gait data, thereby reducing both complexity and computational burden [40]. This approach enhances interpretability, allowing for a focused analysis of the key factors contributing to the outcome variable. Furthermore, it facilitates a deeper understanding of the underlying mechanisms with meaningful clinical implications. However, it is crucial to interpret feature selection results with caution and care.

Our research has a number of limitations that must be acknowledged. Firstly, the small sample size used in this study may limit the generalizability of our findings. As such, larger future studies are necessary to validate our results. Additionally, we did not conduct a comprehensive gait analysis to fully elucidate the differences between the groups. Even the knee and hip OA groups did share similarities in age, sex, and height, the knee OA participants exhibited higher BMIs and varied KOOS/HOOS scores. While we can attribute these observations to the distinct anatomical characteristics and biomechanical differences associated with these joints, it is plausible that the knee OA group in our study may have been at a different disease progression stage compared to the hip OA group, contributing to variations in symptom severity and functional limitations.

Despite the limitations, our study demonstrates the potential of wearable sensors in differentiating between knee and hip OA gait patterns. This capability represents a significant advancement in the at-home patient monitoring and rehabilitation. This distinction holds relevance in various settings where gait analysis plays a crucial role, including orthopedic clinics, rehabilitation centers, and research studies focusing on OA. Moreover, our findings inspire further exploration of sub-pathologies within the hip and knee, for instance, distinguishing between hip OA and greater trochanteric pain syndrome or discriminating between patients with medial and lateral knee OA. Investigating these subgroups can provide valuable insights into the diverse presentations observed within the OA population.

5. Conclusion

In conclusion, our study shows that wearable sensors can distinguish gait patterns in individuals with hip and knee OA, supporting potential clinical use for diagnosis, treatment planning, and monitoring. Future studies must confirm findings and explore clinical implications.

Declaration of generative AI in scientific writing

During the preparation of this work the authors used Grammarly in order to review spelling, grammar, punctuation, and language clarity. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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CRediT authorship contribution statement

Arash Ghaffari: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing. **Pernille Damborg Clasen:** Data curation, Investigation, Methodology, Writing – original draft, Writing – review & editing. **Rikke Vindberg Boel:** Data curation, Investigation, Methodology, Writing – original draft, Writing – review & editing. **Andreas Kappel:** Conceptualization, Methodology, Supervision, Writing – original draft, Writing – review & editing. **Thomas Jakobsen:** Conceptualization, Methodology, Supervision, Writing – original draft, Writing – review & editing. **John Rasmussen:** Conceptualization, Formal analysis, Methodology, Project administration, Supervision, Validation, Writing – original draft, Writing – review & editing. **Søren Kold:** Conceptualization, Project administration, Resources, Supervision, Validation, Writing – original draft, Writing – review & editing. **Ole Rahbek:** Conceptualization, Formal analysis, Project administration, Resources, Supervision, Validation, Writing – original draft, Writing – review & editing.

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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