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Feasibility of automatic knee kinematic feature learning for discriminating between individuals with and without a history of an anterior cruciate ligament reconstruction

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ABSTRACT

Background: Knee osteoarthritis is a degenerative joint disease that often develops following an anterior cruciate ligament (ACL) injury, even following surgical reconstruction (ACLr). This research evaluated whether biomechanical biomarkers, derived from wearable sensors, could differentiate people with an ACLr, who are at risk of early knee osteoarthritis, from healthy controls.

Methods: Twelve participants with an ACLr and 19 controls participated. Continuous three-dimensional (3D) knee kinematics were captured using inertial measurement unit (IMU) sensors during sequential daily living tasks comprising sit-to-stand, walking, obstacle crossing, squatting, and stand-to-sit. Using a least absolute shrinkage and selection operator regression model, 468 knee time-series features were extracted to classify individuals with an ACLr from controls. Cohen's *d* effect sizes were calculated for features selected by the regression model to quantify between-group differences.

Findings: The model achieved an accuracy of 80.7 %, with 92 % sensitivity and 74 % specificity. Seven features were retained from the model. The top two features with the greatest effect sizes when compared to controls were: a reduction in peak-to-peak knee axial rotation and maximum knee axial rotation angle ($d = 1.35$ and $d = 1.31$, respectively).

Interpretation: The present study found that axial knee kinematics could serve as important biomarkers of an ACLr, potentially representing a modifiable feature for osteoarthritis treatment and prevention. These findings demonstrate the feasibility of early knee osteoarthritis detection using biomechanical biomarkers, providing preliminary evidence for the use of wearable sensors outside clinical settings and underscoring the possibilities for at-home monitoring.

1. Introduction

Osteoarthritis (OA) is a degenerative joint disorder characterised by the breakdown of articular cartilage, changes in subchondral bone, and synovial inflammation resulting in pain, swelling, and decreased function (Martel-Pelletier et al., 2016). OA is one of the leading global causes of disability (Steinmetz et al., 2023), and places considerable burdens on healthcare systems (Lo et al., 2021). While OA can affect various joints, knee OA is the most prevalent form, posing a significant burden on mobility and quality of life (Hunter and Bierma-Zeinstra, 2019).

Several factors contribute to knee OA risk, including traumatic joint injury and obesity. (Martel-Pelletier et al., 2016). Among these risk factors, anterior cruciate ligament (ACL) injuries are a major risk factor for early OA development, with ACL injuries affecting around 1 in every 3500 people (Beynnon et al., 2005). Knee OA symptoms typically manifest approximately 5–10 years earlier, following ACL injuries

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(Risberg et al., 2016). Interestingly, the risk of early knee OA remains the same for ACL-injured individuals regardless of whether they had surgical reconstruction or not, with both populations facing a fourfold higher likelihood of developing knee OA compared to non-injured individuals (Poulsen et al., 2019). Given the increased susceptibility of anterior cruciate ligament reconstructed (ACLr) populations to knee OA, this population offer a lens through which biomarkers of early knee OA can be discovered.

Biomechanical features combined with machine learning (ML) represent a promising biomarker for early detection of knee OA, particularly for high-risk individuals such as those with ACLr (Xuan et al., 2023). There is significant evidence that individuals with knee OA and/or those with ACLr have altered motor patterns when compared to healthy individuals, and that these alterations worsen with symptom and structural severity (Duffell et al., 2014; Mills et al., 2013). Biomechanical alterations observed in people with established knee OA have also been reported in people with ACLr. For example, patients within 1 year of an ACLr exhibited similar ground reaction force (GRF) profiles to individuals with mild knee OA (Kallgren-Lawrence [KL] 2) (Bjornsen et al., 2024). Also, individuals with an ACLr have been shown to walk with a greater external knee adduction moment compared to healthy controls (Butler et al., 2009), similar to individuals with knee OA (Foroughi et al., 2009).

Despite the plethora of studies that have looked for differences in the biomechanics of people with OA versus ACLr, biomechanical features have only recently been used as a tool to discriminate people at different stages of the OA disease spectrum, including those with ACLr (Long et al., 2017). For example, a study measuring GRF using a force plate and a random forest classifier could discriminate people with knee OA (no structural severity reported) from healthy controls with an accuracy of 72 % (Kotti et al., 2017). One study, using optical motion capture with force plates to measure both kinematics and kinetics and a k nearest neighbour (kNN) classifier to distinguish knee OA (mixed KL grades) from healthy controls (Long et al., 2017), reported an Area Under the Receiver Operating Curve (AUC) ranging from 0.47 when using one biomechanical feature rising to 0.92 when using multiple biomechanical features as predictors. Another study, measuring kinematic features of the lower limb using an optical motion capture system and neural networks classifying ACL-deficient individuals from healthy controls (Zeng et al., 2020), achieved an accuracy of 62 %. Yet another study that measured kinematic and kinetic features of the lower limb collected via optical motion capture and force plates achieved an accuracy of discriminating individuals with an ACLr from healthy controls by 94 % using a Support Vector Machine (Kokkotis et al., 2022).

Current biomechanical methods used to classify knee OA or at-risk of OA patients have several limitations. First, many rely on expensive equipment like force plates (Kotti et al., 2017), or combining force plates with optical motion capture (Kokkotis et al., 2022; Long et al., 2017). This reliance on force plates means that motor assessments are restricted to small numbers of individuals, and in specialised clinics or laboratories. Second, traditional methods of motion capture require a time-consuming process of marker placement on anatomical landmarks, and extensive amounts of data processing (e.g., marker labelling, gap filling, modelling, and careful segmentation of the signal between distinct events). Third, current methods assessed biomechanical changes during a single motor task, most commonly walking (Kokkotis et al., 2022; Kotti et al., 2017), whereas biomechanical alterations in people with OA are not restricted to a single motor task (Anan et al., 2015). Inertial measurement units (IMUs) provide an alternative, valid, and reliable method for the kinematic analysis of movement, compared to traditional motion capture (Poitras et al., 2019). IMUs requiring less time to prepare and process data do not require participants to be constrained within a small capture volume, thereby allowing the assessment of multiple motor tasks (Kadirvelu et al., 2023).

This study aims to determine whether the automatic feature extraction from three-dimensional (3D) knee kinematics can effectively differentiate individuals with an ACLr, who are at risk of developing early knee OA, from healthy controls. A secondary aim is to discover which kinematic features discriminated individuals with an ACLr from healthy controls. Methodologically, the main novelty of this study is that we adopted a data-driven approach to extract discrete features from 3D knee kinematics time-series signals collected with a pair of IMUs during a continuous sequence of motor tasks. This contrasts with current biomechanics research, where participants have to repeat standardised motor tasks, and researchers must segment the data to identify discrete measures (Butler et al., 2009). We hypothesised that knee kinematics can discriminate ACLr from healthy controls during sequential daily living tasks with an accuracy of >70 % (Kotti et al., 2017). We also hypothesised that knee axial kinematic features would be the strongest factors that discriminated between the two groups (Kaur et al., 2016).

2. Methods

2.1. Research design

This was a cross-sectional laboratory study involving both individuals with an ACLr and healthy controls. Ethical approval for this study was obtained from the University of Essex Research Ethics Committee (Reference: ETH2324–1906). Participants were recruited from the general public via word of mouth, printed advertisements around the University of Essex campus, and using social media platforms. Data collection took place between October 2024 and February 2025. Before participation, all individuals provided written informed consent.

2.2. Participants

Participants were eligible to be in the ACLr group if they met the following criteria: aged 18–40 years, had undergone ACL reconstructive surgery at least 12 months before the study, and had not experienced lower-limb pain intensity exceeding 2/10 (where 0 represents no pain and 10 represents maximal intolerable pain) in the three months before participation. Exclusion criteria for this group included a self-reported history of lower extremity orthopaedic surgery before the ACL surgery, having undergone multi-ligament knee surgery at the time of the ACL procedure, and a current diagnosis of knee OA. For the healthy control group, participants aged 18–40 years old were required to have no history of lower extremity injury or surgery and no experience of lower-limb pain intensity greater than 2/10 during the three months before the study. For both groups, participants were excluded if they were pregnant, had cardiovascular or neurodegenerative conditions, or had a BMI over 35 kg/m^2.

2.3. Self-reported descriptive characteristics

Demographic characteristics, such as age, sex, height, weight, and physical activity levels, were collected for all participants. For the ACLr group, additional questions about their ACL history and any surgeries were collected. The KOOS-42 was collected for all participants; this is a self-reported outcome measure consisting of 42 items generating a score ranging from 0 to 100, with higher scores indicating better knee function and less pain (Roos and Lohmander, 2003). This scale has high internal consistency, with Cronbach's alpha values ranging from 0.82 to 0.98, and strong test-retest reliability (ICC's between 0.80 and 0.96) (Bekkers et al., 2009).

2.4. Movement task

Nine IMU sensors (Noraxon Ultium™, USA, 200 Hz) were placed on the upper thoracic spine, lower thoracic spine, pelvis, bilateral thighs (left and right), bilateral shanks (left and right lower legs), and bilateral feet (left and right), according to the manufacturer's guidelines. A functional calibration procedure was performed, and the data were

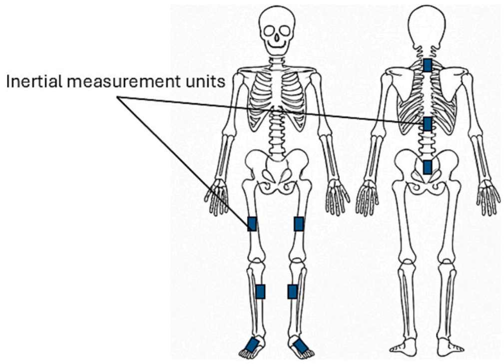

Fig. 1. Placement of the nine inertial measurement units of the trunk and bilateral lower-limbs.

acquired using myoResearch software (vMR4 4.0.22, Noraxon, USA). Two of these IMU sensors (thigh, shank) were used to quantify knee kinematics of the selected limb for subsequent analysis.

Participants were instructed to complete five repetitions of a movement task sequence (Fig. 1). From a seated position (point a), participants stood up and walked 7 m, during which they navigated a 20 cm step (point b). Upon reaching the end of the walking path, they performed a maximal deep knee squat, which involved bending their knees to the lowest comfortable position while maintaining balance and control (point c). Following the squat, participants walked back 7 m to the original chair, once again crossing the 20 cm step end route. The sequence was selected to simulate a range of everyday activities, such as step negotiation and deep squatting, which are particularly relevant to individuals with knee OA. Participants were free to select which leg to place on the step, and which direction to turn (clockwise or counter-clockwise) for the return, to mimic free-living conditions where people move differently based on different internal (e.g. strength) and external factors (e.g. encountered obstacle height). Short rest periods of 1 min were provided between repetitions to minimise fatigue and ensure consistent performance across trials. Three-dimensional (3D) kinematics were collected as a continuous time series across the five repetitions, including rest periods.

2.5. Data processing

Data analysis was conducted using R statistical software (version 4.4.2). For each participant, 3D knee angle signals were extracted from the affected knee in the ACLr group and the dominant (side used to kick a ball) leg in the control group. For each time-series signal, 156 features were extracted. The *Time Series Feature Extraction Library (TSFEL)* Python package was used to calculate statistical, temporal, fractal and spectral features (Barandas et al., 2020): temporal features include trends, cycles, and correlations in sequential data; statistical features include mean, variance, skewness, and kurtosis; spectral features include periodicities and frequency components; and fractal features quantify complexity and self-similarity across scales.

2.6. Statistical analysis

All analyses were undertaken using the *nestedcv* R package (version 0.7.12). The outcome to be predicted was the group (ACLr vs control), whilst the extracted time-series features (p = (156 features × 3) 468) represented the predictors. All predictors were scaled to a mean of 0 and a standard deviation (SD) of 1, to ensure different predictors with different scales had an equal opportunity to be selected. LASSO regression is a penalised linear modelling approach that incorporates a shrinkage penalty to enforce sparsity among predictors (Tibshirani, 1996). By applying an L1 penalty, LASSO can reduce some predictor coefficients to zero, effectively performing variable selection while

Table 1
Participant descriptive characteristics.

Variables	Control ($N = 19$[1])	ACLr ($N = 12$[1])
Age (years)	21.7 (3.4)	24.3 (5.1)
Ethnic Origin		
Asian	2 (11 %)	1 (8.3 %)
Black/African/Caribbean	1 (5.3 %)	2 (17 %)
Mixed two or more ethnic groups	1 (5.3 %)	1 (8.3 %)
Other (Arab or any others)	1 (5.3 %)	1 (8.3 %)
White	14 (74 %)	7 (58 %)
Gender		
Male	12 (63 %)	10 (83 %)
Female	7 (37 %)	2 (17 %)
Height (cm)	178 (18)	176 (8)
Weight (kg)	80 (15)	76 (10)
Leg Dominance		
Left	4 (21 %)	2 (17 %)
Right	15 (79 %)	10 (83 %)
ACLr Limb		
Left		4 (33 %)
Right		8 (67 %)
Time Since ACLr		
1 year		5 (42 %)
2 years		4 (33 %)
3–5 years		3 (25 %)
KOOS-Scores		
Symptoms*	94 (8)	76 (14)
Pain*	95 (9)	84 (18)
Activities of daily living*	97.4 (6.4)	92.6 (9.5)
Sport*	89 (16)	75 (22)
Knee-related quality of life*	90 (16)	66 (27)

1Mean (SD); n (%).
Abbreviations: ACLr - anterior cruciate ligament reconstruction, UCLA - UCLA activity scale, KOOS - Knee injury and osteoarthritis outcome score.

enhancing predictive accuracy. The model is estimated using coordinate descent for a given level of shrinkage, controlled by the regularisation parameter λ. A nested cross-validation scheme was used for hyper-parameter tuning and model performance evaluation. A leave-one-out cross-validation (LOOCV) was used as the outer folder for model evaluation, and a 10-fold cross-validation was used to tune the optimal λ value. A Boruta filter was used as a pre-processing step to identify the most important features (Kursa and Rudnicki, 2010). Given the class imbalance in our two groups, we used the synthetic minority over-sampling technique (SMOTE) as a pre-processing step (Chawla et al., 2002).

The following diagnostic performance metrics were calculated: sensitivity $\left(\frac{\textit{True positive}}{\textit{True positive}+\textit{False negative}}\right)$, specificity $\left(\frac{\textit{True negative}}{\textit{True negative}+\textit{False positive}}\right)$, positive likelihood ratio (LR+) $\left(\frac{\textit{Sensitivity}}{1-\textit{Specificity}}\right)$, negative likelihood ratio (LR−) $\left(\frac{1-\textit{Sensitivity}}{\textit{Specificity}}\right)$, and accuracy $\left(\frac{\textit{True negative}+\textit{True positive}}{\textit{Total}}\right)$. For LR+, a value ≥ 2 represents a "slight", ≥ 5 represents a "moderate", and ≥ 10 represents a "large" increase in post-test probability of the presence of a condition (Parikh et al., 2009). For LR-, a value ≤ 0.5 represents a "slight", ≤ 0.2 represents a "moderate", and ≤ 0.1 represents a "large" decrease in the post-test probability of the presence of a condition (Parikh et al., 2009). For the predictors that were selected from the LASSO model, Cohen's d $\left(\frac{\textit{Mean1}-\textit{Mean2}}{\textit{SDpooled}}\right)$ was calculated using the *easystats* R package (version 0.7.3) to assess the effect size of the differences between groups with thresholds determined at $d \geq 0.2$ (small), $d \geq 0.5$ (medium), and $d \geq 0.8$ (large) (Gignac and Szodorai, 2016).

3. Results

Twelve participants with ACLr and 19 controls participated. Table 1 summarises the descriptive statistics for these participants, including

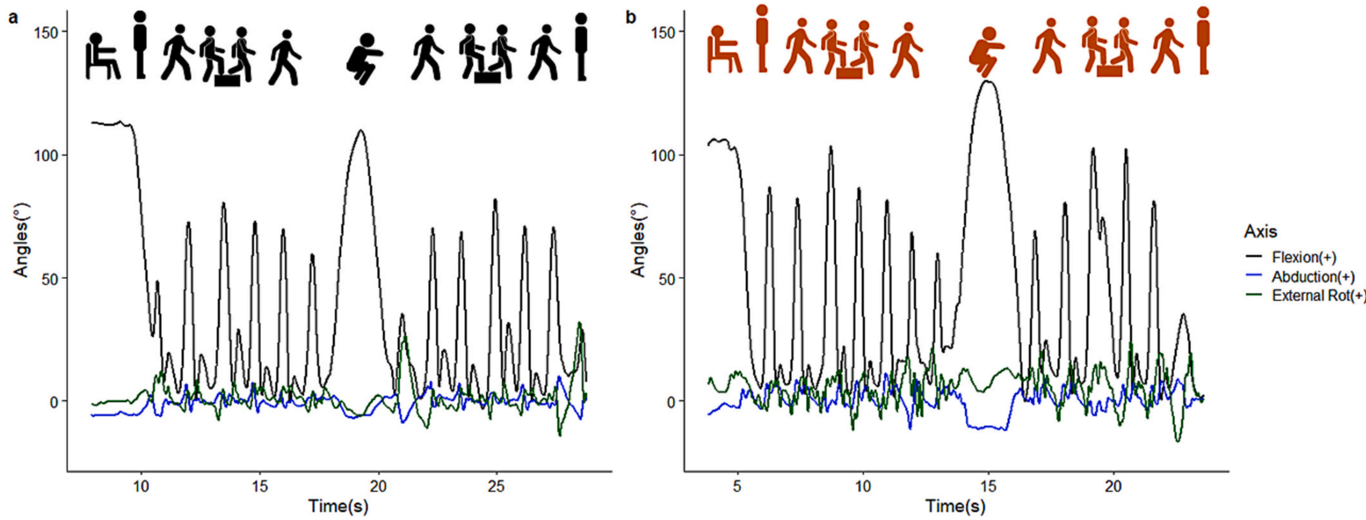

Fig. 2. Time-series of the three-dimensional knee angles of a) the dominant limb of a healthy participant, and b) the operated limb of a participant with an anterior cruciate ligament reconstruction, for a single sequence of motor tasks.

Table 2
Confusion matrix.

	Observed	
Predicted	ACLr group (+)	Control group (−)
ACLr group (+)	11	5
Control group (−)	1	14

demographics, ACLr-specific questions, UCLA activity levels, and KOOS functional outcomes. Fig. 2 illustrates a continuous time-series of the 3D knee kinematics of a single participant. The 3D knee kinematic time-series of the assessed limb can be found in the supplementary material.

Table 2 illustrates the predicted confusion matrix. The LASSO model had a sensitivity of 92 % (95 % CI: 62 %–1 %) and a specificity of 74 % (95 % CI: 49 %–91 %). The LR+ was 3.48 (95 % CI: 1.61–7.53), indicating a moderate increase in post-test probability of ACLr with a positive result, while the LR- was 0.11 (95 % CI: 0.02–0.75), suggesting a substantial reduction in ACLr likelihood with a negative result. The test demonstrated 80.7 % overall accuracy and an area under the receiver operating curve (AUC) of 0.80.

From the original 468 kinematic predictors, the LASSO model selected seven predictors within the final model (Fig. 3). Of the chosen predictors, only autocorrelation of the knee frontal plane angle predicted a reduction in the log-odds of being in the ACLr group. In contrast, all other features predicted an increase in the log-odds of being in the ACLr group. The most important predictors were related to axial knee motion, with peak-to-peak (PTP) knee axial rotation angle and maximum knee axial angle showing the highest importance scores. A one SD decrease in PTP knee axial rotation was associated with a 0.23 increase in the log-odds of being in the ACLr group (Fig. 3). Also, a one SD decrease in maximum knee external rotation angle resulted in a 0.18

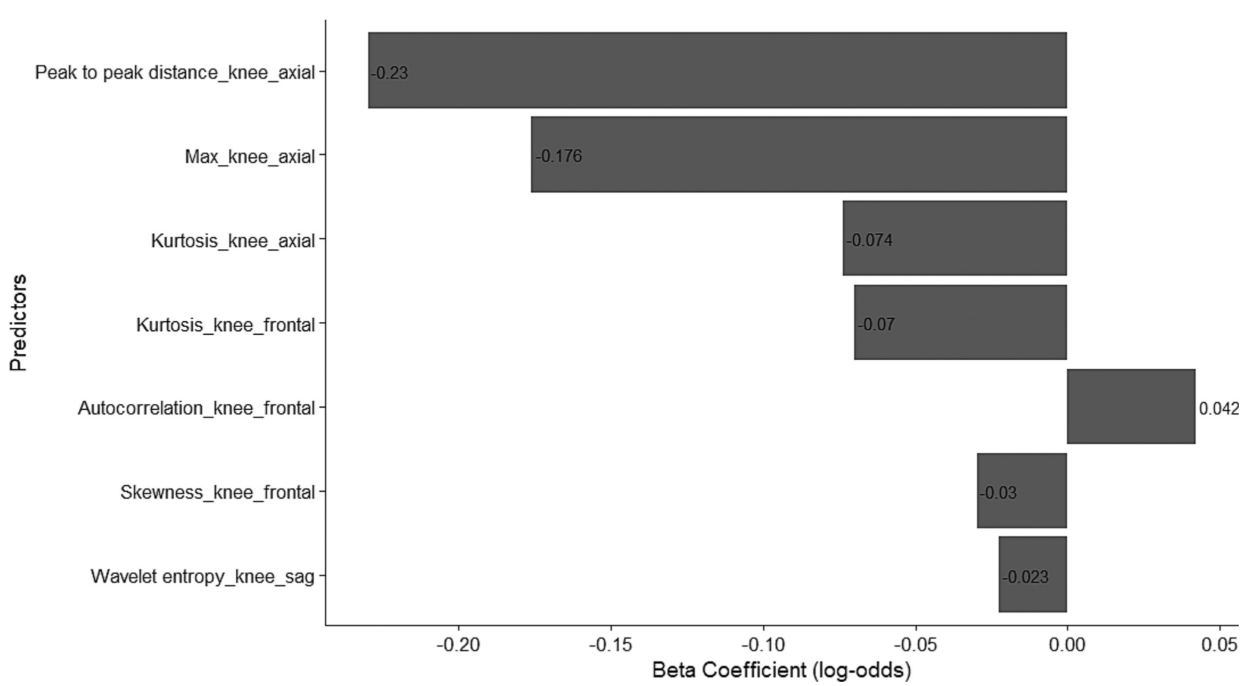

Fig. 3. Magnitude of beta coefficient of selected predictors.

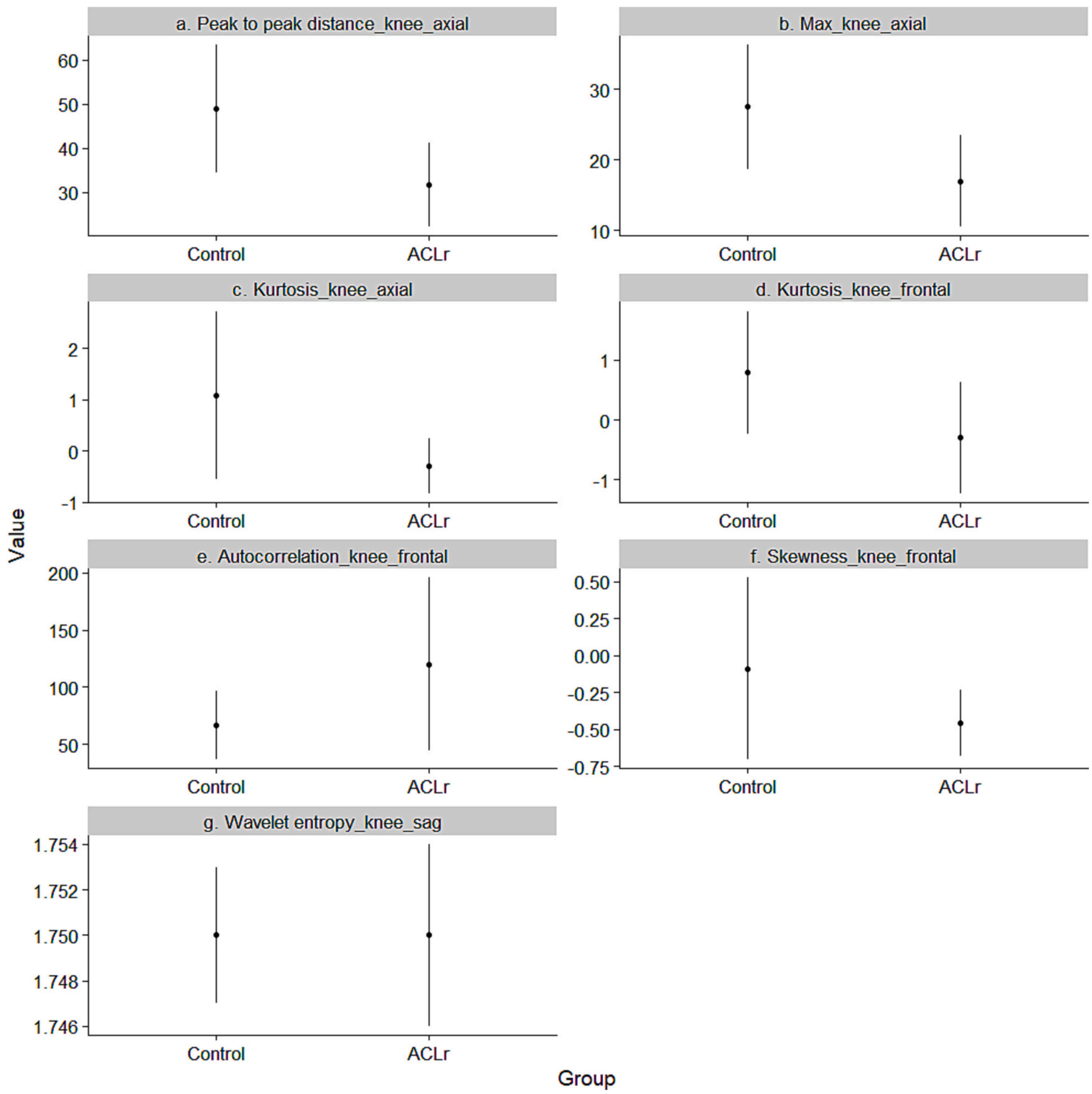

Fig. 4. Mean (error bars of one standard deviation) of each of the predictors selected by the LASSO model.

increase in the log-odds of being in the ACLr group (Fig. 3).

PTP knee axial rotation was significantly lower in the ACLr group compared to the control group by a large effect size ($d = 1.35$ [95 %CI 0.54–2.14]) (Fig. 4a, Table 3), followed by maximum knee axial rotation angle ($d = 1.31$ [95 %CI 0.51–2.10]) (Fig. 4b, Table 3), and Kurtosis of knee axial rotation angle ($d = 1.03$ [95 %CI 0.25–1.79]) (Fig. 4c, Table 3). Kurtosis of the knee frontal plane angle, skewness of the knee frontal plane angle, and wavelet entropy of the knee sagittal angle were decreased in the ACLr group vs the control group by effect sizes of $d = 1.10$ (95 %CI 0.32–1.87) (Fig. 4d, Table 3), $d = 0.74$ (95 %CI -0.01–1.48) (Fig. 4f, Table 3), and $d = 1.07$ (95 %CI 0.29–1.83) (Fig. 4g, Table 3), respectively. Autocorrelation of the knee frontal plane angle was higher in the ACLr group compared to the control group by an effect size of $d = 1.03$ (95 %CI 0.25–1.79) (Fig. 4e, Table 3).

4. Discussion

This study explored novel methodologies for detecting early knee OA using biomechanical biomarkers. In support of our hypothesis, that knee kinematics from two IMUs can discriminate ACLr from healthy controls with an accuracy of >70 %, our method demonstrated a sensitivity of 92 %, a specificity of 74 %, and an accuracy of 80.7 %, supporting the utility of biomechanical biomarkers in distinguishing ACLr individuals from healthy controls. The results illustrate how the model is more likely to incorrectly classify healthy individuals as ACLr than to miss true ACLr cases. In clinical screening scenarios, this trade-off is preferred where high sensitivity to capture the ACLr individual is prioritised over minimising false positives. Also, in support of our hypothesis, knee axial kinematic features were the most discriminative features discovered from our model.

The present model's performance was superior to that of several previous studies (Kotti et al., 2017; Zeng et al., 2020), but inferior to others (Kokkotis et al., 2022; Long et al., 2017). There was a trend that better-performing prediction models incorporated multiple joint-level kinetic features into their models (Kokkotis et al., 2022; Long et al., 2017). In contrast, poorer predictive performances either relied on kinematics only (Zeng et al., 2020) or whole-body kinetic features, such as GRF (Kotti et al., 2017). Incorporating multiple joint-level kinetics as predictors may increase the predictive performance of models, given that people with ACLr or knee OA have altered joint-level kinetics not only at the knee, but at other joints within the kinetic chain (D'Souza et al., 2022; Lepley and Kuenze, 2018). However, quantifying joint kinetics requires combining optical motion capture with force plates, which makes data collection and processing more costly and time-

Table 3
Clinical interpretation of the features selected.

Feature selected	Clinical interpretation
Peak to peak distance_knee_axial	Maximum minus minimum value of knee axial rotation angle (i.e. range of motion). ACLr has lower knee axial plane ROM than controls.
Max_knee_axial	Maximal knee external rotation angle. ACLr has a lower maximal knee external rotation angle than controls.
Kurtosis_knee_axial	High positive value indicates greater distribution in the tail region, reflecting greater presence of extreme values of the knee axial plane angles. ACLr has fewer extreme knee axial plane angles than controls.
Kurtosis_knee_frontal	High positive value indicates greater distribution in the tail region, reflecting greater presence of extreme values of the knee frontal plane angles. ACLr has fewer extreme knee frontal plane angles than controls.
Autocorrelation_knee_frontal	High autocorrelation means a strong tendency for knee frontal plane angle to be correlated with their past values – i.e. greater predictability. ACLr has greater predictability of the knee frontal plane angle than controls.
Skewness_knee_frontal	Positive value means the bulk of the data is distributed on the left side of the distribution (i.e. more knee adduction). ACLr spends more time with their knee in a more abducted position than controls.
Wavelet entropy_knee_sag	A higher wavelet entropy value at a particular scale suggests a greater presence of unpredictable or irregular activity. ACLr has less unpredictability of the knee sagittal plane angle than controls.

consuming. An advantage of relying only on knee joint kinematic features is that it only utilises a pair of IMUs, potentially paving the way for OA risk assessment outside of the laboratory setting. Additionally, the use of a heterogeneous set of activities of daily living (e.g., step navigation) in the present study means that the features are task-agnostic.

Studies on biomechanical alterations in people with knee OA or ACLr have focused significantly on sagittal and frontal plane knee features (Kaur et al., 2016; Kokkotis et al., 2022; Long et al., 2017). Interestingly, the two most important predictors identified in this study were related to axial plane kinematics, consistent with research emphasising the ACL's critical role in regulating rotational stability of the knee (Andersen and Dyhre-Poulsen, 1997). Furthermore, the present study found that the knee external rotation angle was reduced by a large effect size in ACLr individuals compared with healthy controls. This supports a previous study, which found less knee external rotation angle in people with ACLr during stair descent compared to controls (Gao et al., 2012). Full restoration of rotational knee stability post-ACLr is rare, with studies noting that 'overtightening' of the graft reduces knee axial rotation beyond 10° of knee flexion, leading to constrained or asymmetric mechanics (Brandenburg and Matelic, 2018; Zee et al., 2020). These altered knee axial plane kinematics can disrupt normal knee forces and their distribution, potentially accelerating cartilage wear and increasing the risk of early knee OA (Andersen and Dyhre-Poulsen, 1997).

The present study also found that frequency-domain variables represent some of the more important predictors of ACLr. The significant reduction in these metrics within the ACLr group suggests a more constrained and less dynamic movement pattern (Zakaria et al., 2013), indicating a shift towards more regular and less variable kinematics. This finding aligns with previous research showing decreased gait variability in ACL-deficient knees, where reduced variability is thought to reflect a more rigid movement strategy, likely as a result of the loss of mechanical restraint and proprioceptive input from the ACL (Georgoulis et al., 2010). Interestingly, pre- and post-ACLr studies indicate reduced movement variability pre-operation, likely as a protective strategy, with a post-operative increase in movement variability potentially reflecting diminishing joint adaptability (Moraiti et al., 2007; Moraiti et al., 2010). The similar patterns observed across other wavelet variables, such as wavelet energy and standard deviation at 50 Hz in knee axial rotation, further support the notion of restricted knee motion following ACLr (Georgoulis et al., 2010). In line with the optimal variability hypothesis (Stergiou et al., 2006), a lower variability and reduced complexity in knee kinematics, may reflect a strategy to stabilise the joint, but could also indicate reduced flexibility and responsiveness to environmental demands (Georgoulis et al., 2010). This reduction in movement variability could potentially increase the risk of the development of knee OA over time.

Given that the present work served as a feasibility study, a formal sample size calculation was not undertaken. Hence, the results from this study reflect hypotheses generation to be tested in future research. In addition, the present study included a small sample size, which may restrict the generalisability of the findings. Findings from this feasibility study can be used to perform sample size calculations for future diagnostic research using biomechanical features. A second limitation of the present study was that joint cartilage health was not quantified using magnetic resonance imaging. Future studies to determine whether biomechanical features can predict specific knee cartilage degenerative features are warranted. Lastly, the cross-sectional design of the present study limits insights into disease onset and progression. Longitudinal studies incorporating imaging modalities such as MRI are needed to assess structural changes over time and their relationship with the biomechanical biomarkers identified in this study.

5. Conclusion

Biomechanical biomarkers during daily living tasks were able to discriminate between individuals with ACLr and healthy controls, capturing not only group differences but also key alterations in joint mechanics. The moderate LR's suggest that such biomarkers cannot be relied on alone for the detection of early knee OA. The present study found that axial knee kinematics could serve as important biomarkers of early risk of knee OA, potentially representing a modifiable feature for OA treatment and prevention. With advancements in wearable sensor technologies capable of capturing joint kinematics in real-world settings and from home, there is a growing opportunity to develop efficient, non-invasive screening methods for early knee OA detection and monitoring outside of the clinical setting.

CRediT authorship contribution statement

Benjamin R. Butler: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **Behnam Gholami:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Methodology, Formal analysis, Data curation. **Benedict Z.W. Low:** Writing – review & editing, Writing – original draft, Validation, Supervision, Project administration. **Qichang Mei:** Writing – review & editing, Writing – original draft, Visualization, Validation, Conceptualization. **David Hollinger:** Writing – review & editing, Visualization, Validation, Software, Project administration, Methodology. **Zainab Altai:** Writing – review & editing, Visualization, Validation, Supervision, Project administration. **David W. Evans:** Writing – review & editing, Writing – original draft, Validation, Conceptualization. **Bernard X.W. Liew:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

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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.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.clinbiomech.2025.106673.

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