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Feasibility of human ethomic biomarkers for the diagnosis and monitoring of hip osteoarthritis

Bernard X.W. Liew [a,*], David Rugamer [b], Bradley S. Neal [a], Aleksandra Birn-Jeffery [a], Qichang Mei [c,d], Harry Roberts [e], Nelson Cortes [a,f]

[a] School of Sport, Rehabilitation and Exercise Sciences, University of Essex, Colchester, Essex, United Kingdom
[b] Department of Statistics, Ludwig-Maximilians-Universität München, Germany
[c] Faculty of Sports Science, Ningbo University, Ningbo, China
[d] Auckland Bioengineering Institute, The University of Auckland, Auckland, New Zealand
[e] School of Biosciences, University of Surrey, Guildford, United Kingdom
[f] Department of Bioengineering, George Mason University, Fairfax VA, USA

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ABSTRACT

Radiographic imaging is typically used to diagnose osteoarthritis (OA). However, patients would typically be sent for imaging after they present to a physician because of joint pain. By this time, the condition is likely irreversible. This study aims to determine if human ethomics (i.e. behavior) defined by whole-body kinematics during walking, can be used as a diagnostic biomarker of hip OA. Three-dimensional motion capture was performed on 106 participants with unilateral hip OA and 80 asymptomatic participants (N = 80) during walking. Sixteen sagittal plane joint angle variables were extracted and used as inputs into the prediction model. The categorical outcome was the radiographic severity of hip OA using the Kallgren-Lawrence (KL) scale (0 [no OA], 2, 3, 4[worse]). Functional data boosting was used for statistical modelling with bootstrap resampling. Our ethomics approach to hip OA diagnosis had positive likelihood ratio (LR+) values ranging from 4.79 (95 %CI 3.20, 7.42) to detect the presence of KL3, to 43.95 (95 % CI 14.9, 76.08) to detect the presence of any OA. The present approach had negative likelihood ratio (LR−) values ranging from 0.56 (95 %CI 0.33, 0.79) of 0.07 (95 % CI 0.04, 0.11) to detect the absence of KL4, to 0.07 (95 %CI 0.04, 0.11) to detect the absence of any OA. Human ethomics represents an ideal candidate for OA biomarkers that could overcome many of the logistical challenges of traditional imaging and biochemical biomarkers.

1. Introduction

Osteoarthritis (OA) is one of the leading global causes of pain and disability (Vos et al., 2020). One in nine adults in England over 45 years of age has hip OA, characterised by slow structural and symptomatic progression, with up to 30 % eventually requiring a joint replacement (Burn et al., 2019). A diagnosis of OA is usually triggered by the onset of symptoms, but by the time OA is ascertained via radiological imaging, it is likely irreversible (Glyn-Jones et al., 2015). Although still not available in the pharmaceutical market, significant research is ongoing to develop drugs that actively modify the disease process (Cho et al., 2021). For such disease-modifying drugs to be effectively administered, a diagnosis of OA must occur earlier, before the onset of symptoms (Glyn-Jones et al., 2015; Mahmoudian et al., 2021).

The diagnosis and monitoring of OA are challenging given that many clinical tools rely solely on subjective patient history and outcome measures (Metcalfe et al., 2019; Quintana et al., 2007), clinical “by eye” or “by hand” assessments (Holla et al., 2012), and clinical classification criteria (e.g. the American College of Rheumatology [ACR] criteria) (Altman et al., 1991). For example, a reduced hip adduction range of motion (ROM) has a positive likelihood ratio (LR+) of 4.2 and a negative likelihood ratio (LR−) of 0.25 (Metcalfe et al., 2019), a self-report of the worst pain in the medial thigh region a LR+ of 7.8 and LR− of 0.89 (Metcalfe et al., 2019). When combining self-report and physical assessment findings, the presence of four or more clinical signs can achieve a LR+ for hip OA of 4.9 (Metcalfe et al., 2019). Hip ROM assessed manually using a goniometer achieved a diagnostic performance, relative to radiographic imaging, of 4.2 (LR+) and 0.88 (LR−)

* Corresponding author.
E-mail address: bl19622@essex.ac.uk (B.X.W. Liew).

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(Holla et al., 2012). A disadvantage of subjective questions for diagnosis is that they are reliant on accurate subjective recall, and may be confounded by factors beyond the intrinsic pathology of OA, such as psychological distress (Lentz et al., 2020) and pain (Guérard et al., 2020). Manual physical assessments, like goniometry, may become time-consuming to conduct if performed beyond a single joint.

To circumvent the limitations of traditional clinical tools, researchers have begun searching for biomarkers that allow early diagnosis of OA (Hunter et al., 2023; Lotz et al., 2013). Currently, the two most investigated potential biomarkers of OA can be classified either as imaging or biochemical markers (Lotz et al., 2013). Neither of these biomarker types is easily translated in the clinical setting as they are either very expensive or invasive. An untapped biomarker type that can overcome these limitations is human ethomics (i.e., the study of behaviour). Human ethomics represents a potentially ideal biomarker candidate as it can be quantified objectively with both laboratory-grade motion capture systems, and lower-cost digital devices, such as smart portable devices. Ethomic biomarkers are currently limited in their utility as diagnostic OA biomarkers, primarily because they are often reflect traditional clinical measures – for example, step counting (Lo et al., 2015). To fully realise the potential of discovering ethomic OA biomarkers, artificial intelligence (AI) must be exploited.

People with hip OA adopt different movement and motor strategies compared to asymptomatic cohorts, and these altered strategies worsen with greater OA severity (D'Souza et al., 2022; Diamond et al., 2024; Franco et al., 2021; Steingrebe et al., 2023). Trunk and lower-limb kinematics during walking were able to differentiate between people with and without hip OA with an accuracy of >90 % when using a Support Vector Machine (SVM) classifier – a machine learning (ML) technique (Laroche et al., 2014). Meyer et al., (Meyer et al., 2015) have used a combined Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) approach, reporting that biomechanical features could achieve a discriminatory value of >0.86 (Area under the Receiver Operating Curve), with reduced hip/knee extension angles the features with the greatest discriminatory power (Meyer et al., 2015). Joint kinematics alone have been able to achieve a LR+ and LR− of 6.9 and 0.95, respectively, when differentiating end-stage hip OA against an asymptomatic control (Emmerzaal et al., 2022). Others have used multivariate functional PCA (MFPCA) of biomechanical waveforms to predict biochemical indices of hip joint cartilage in people with and without OA (Roach et al., 2021). Biomechanical features that are common to both established OA and those at risk of OA could present candidate biomarkers used for the early diagnosis of OA (Bjornsen et al., 2024).

Although many studies have reported gait alterations in people with OA, many fewer have used such alterations for discriminating OA across the severity spectrum, and no studies, to the authors' knowledge have done so using predictive models that are fully transparent and interpretable. The present study aimed to determine the feasibility of human ethomics for the diagnosis and monitoring of the radiographic severity of hip OA, using Functional data Boosting – a fully transparent and interpretable machine learning method (Brockhaus et al., 2020). We focused on laboratory-collected whole-body kinematic features as predictors of a diagnosis of hip OA, to demonstrate the feasibility of ethomic biomarkers that could classify hip OA radiographic severity. We hypothesised that the diagnostic performance of biomechanical features for the diagnosis of radiographic hip OA would exceed the LR+ value of 4.9, achieved by using clinical diagnosis.

2. Methods

2.1. Design

This is a secondary analysis of an open-access dataset (Bertaux et al., 2022) containing 80 asymptomatic participants and 106 participants with unilateral hip OA, identified using the American College of Radiology Criteria (Altman et al., 1991). Full details of the study protocol are reported in the original manuscript (Bertaux et al., 2022) and are summarised below. No ethics approval was required due to the secondary analysis design of the present study.

2.2. Data collection

Three-dimensional (3D) biomechanical analysis of comfortable speed barefooted walking was performed with eight optoelectronic cameras (Vicon MXT40, Vicon, UK; 100 Hz) and two ground-embedded force plates (OR6-5, AMTI, USA; 1000 Hz). Walking trials occurred over a six-metre walkway, using the verbal instruction of "walk as naturally as possible, looking forward". A minimum of ten successful gait trials per participant were recorded.

Reflective markers were placed to create a whole-body Plug-In-Gait (PiG) model (Davis et al., 1991). Marker trajectories were filtered using a lowpass 4th-order Butterworth (10 Hz), whilst ground reaction forces (GRFs) were filtered using a lowpass 2nd-order Butterworth (50 Hz). Gait events of initial contact and toe-off were determined using a kinematic-based algorithm based on the velocities of the foot markers (Zeni et al., 2008). Joint kinematics were computed using the PiG model in Vicon Nexus software (Davis et al., 1991), and we retained only the sagittal plane kinematics for subsequent analysis. This is because non-sagittal plane kinematics are inaccurate using the PiG model (Bertaux et al., 2022).

For the asymptomatic cohort, the right-sided kinematics were time-normalised from the right initial contact to the next consecutive right initial contact. The left-sided kinematics were time-normalised from the left toe-off to the next consecutive toe-off. For the OA cohort, the kinematics of the affected lower-limb were time-normalised between two consecutive initial contacts of the affected lower-limb (right for right OA and left for left OA); whilst the non-affected limb kinematics were time-normalised between two consecutive toe-offs of the non-affected lower-limb (left for right OA, and right for left OA). To temporally align the kinematic waveforms for all participants, we labelled the right limb kinematics for the asymptomatic cohort, and the affected limb kinematics of the OA cohort as the "ipsilateral" side kinematics. We also labelled the left limb kinematics for the asymptomatic cohort and the non-affected limb kinematics of the OA cohort as the "contralateral" side kinematics.

2.3. Statistical approach

A scalar-on-function (SoFR) logistic regression model was used for the multinomial classification of the outcome of hip OA severity (asymptomatic, Kellgren and Lawrence [KL] scale of 2, 3, 4). A SoFR model is one where the outcome contains scalar values (i.e. one participant one value, and the predictors can take on both functional (i.e. the time-series of a single variable for a participant) and scalar values. Functional regression models are extensions of standard regression models, such as generalized additive models (Wood, 2017).

Sixteen sagittal plane angle functional variables from both sides were used as predictors to fit the SoFR model. Variables ranged from neck flexion angle during the ipsilateral stride, to ankle plantarflexion angle of the contralateral limb. All functional variables were scaled to have a mean of zero so that different predictors had equal potential to be included in the model. We used component-wise gradient boosting for model fitting (Brockhaus et al., 2017). The algorithm is an iterative procedure that successively adds one covariate to the model, like a sequential forward stepwise regression, with the ability to handle functional predictors, perform variable selection, and allow for penalized estimation. To estimate the optimal number of iterations to optimize the negative log-likelihood of the multinomial Bernoulli distribution, cross-validation was performed using a 10-fold split cross-validation.

For the multinomial classification of OA severity, we reported the

"one versus all" (e.g., KL3 versus the other three classes) performance metrics, to calculate traditional performance metrics used in the literature for binary diagnostic tests. The following diagnostic performance metrics were calculated: sensitivity $\left(\frac{True positive}{True positive+False negative}\right)$, specificity $\left(\frac{True negative}{True negative+False positive}\right)$, positive predictive value (PPV) $\left(\frac{True positive}{True positive+False positive}\right)$, negative predictive value (NPV) $\left(\frac{True negative}{True negative+False negative}\right)$, LR+ $\left(\frac{Sensitivity}{1-Specificity}\right)$, LR− $\left(\frac{1-Sensitivity}{Specificity}\right)$, accuracy $\left(\frac{True negative+True positive}{Total}\right)$, and odds ratio (OR) $\left(\frac{True positive/False negative}{False positive/True negative}\right)$.

For LR+, a value ≥2 represents a "slight", ≥5 represents a "moderate", and ≥10 represents a "large" increase in posttest probability of the presence of a condition (Jaeschke et al., 1994). For LR−, a value ≤0.5 represents a "slight", ≤ 0.2 represents a "moderate", and ≤0.1 represents a "large" decrease in the posttest probability of the presence of a condition (Jaeschke et al., 1994). For all performance metrics, a 95 % confidence interval (CI) was calculated using a bootstrap resampling approach (with B = 1000 samples).

To visualise the effects, for every functional predictor, the SoFR model estimates the effect of each stride cycle time point on the probability of belonging to one of the four classes. For prediction, this effect is then multiplied by the value of the predictor of this time point, e.g., ipsilateral hip angle, to predict the increase or decrease in probability for each of the four classes. Since the model uses the whole stride information (from 0 to 100 %) to predict the four classes, the model then integrates all time points weighted by their respective effect to obtain the total influence of the functional variable on the outcome.

All analyses were performed using R version 4.3.0, using the "FDboost" package (version 1.1-2) (Brockhaus et al., 2020), and the codes with results are found in the Supplementary material.

3. Results

The descriptive characteristics of the included participants can be found in Table 1. The present study included OA participants with 17.6 % KL2, 46.1 % KL3, and 36.3 % KL4 severity. Healthy participants were significantly younger by 8.1 years ($t = -4.21$, $P < 0.001$), and had a greater BMI 3.7 kg/m^2 ($t = -5.69$, $P < 0.001$), compared to OA participants (Table 1). The mean waveform for each of the predictors, for each of the four classes of OA severity, can be found in the Supplementary material. The optimal number of iterations was 626. Twelve out of the 16 predictors were selected in the final model (Fig. 1). The ipsilateral hip was the most influential predictor, as it contributed to 50.3 % of the reduction of the model's average loss (Fig. 1). The next two most influential predictors were the neck flexion angle during the ipsilateral stride and the ipsilateral ankle plantarflexion angles.

Our ethomics approach to hip OA diagnosis had LR+ values of 43.95 (95 % CI 14.9, 76.08) for the presence of any OA, 10.81 (95 %CI 5.47, 22.78) for the presence of KL2, 4.79 (95 %CI 3.20, 7.42) for the presence of KL3, and 10.20 (95 %CI 4.82, 27.43) for the presence of KL4, respectively (Table 2). This reflects a "large" benefit in increasing the post-test probability of making the correct diagnosis, apart from the classification of KL3, which had a "slight" diagnostic benefit. The present diagnostic approach had LR− values of 0.07 (95 %CI 0.04, 0.11) for classifying KL0 versus all, 0.49 (95 %CI 0.24, 0.74) for classifying KL2 versus all, 0.38 (95 %CI 0.22, 0.55) for classifying KL3 versus all, and 0.56 (95 %CI 0.33, 0.79) for classifying KL4 versus all, respectively (Table 2). This reflects a "large" benefit in decreasing the post-test probability of the presence of any OA, and a "slight" benefit in decreasing the probability that an individual has a KL2/3hip OA (Table 2). An example of how our ethomics approach can be applied clinically is provided using Fagan's nomogram (Fig. 2). Assuming a pre-test probability of hip OA at 35 % (Metcalfe et al., 2019), a positive ethomics finding increases the post-test probability of having hip OA with KL 2 severity to 84 %, whereas a negative finding reduces the post-test probability to 21 % (Fig. 2).

Fig. 3 describes the model's change in estimated probabilities for all four classes during one stride for an "average" person if only a single functional predictor was available. An interpretable plot of all selected predictors can be found in the Supplementary material. Herein, we describe how alterations in the ipsilateral hip kinematic map onto alterations in the predicted class probability. For a healthy person and a person with KL3 OA, the largest increase in probability towards their respective classes occurred at approximately 50 % of the stride cycle (Fig. 3a,c). The ipsilateral hip angle had a greater influence in correctly identifying a healthy person than a person with KL3 OA (Fig. 3a,c). For an OA person with KL2 severity, the largest increase in probability towards a class of KL2 occurred before 25 % of the stride cycle (Fig. 3b). For an OA person with KL4 severity, ipsilateral hip angle shifted the probability of being in this class by a maximum of 6 % over the stride cycle (Fig. 3d).

Table 1
Descriptive characteristics of participants. [a] represent count (proportion) values.

Characteristics	Healthy (n = 80)	KL2 (n = 18)	KL3 (n = 47)	KL4 (n = 37)
Side affected by osteoarthritis[a]				
Left	–	9 (50 %)	16 (34 %)	17 (46 %)
Right	–	9 (50 %)	31 (66 %)	20 (54 %)
Sex[a]				
Female	45 (56 %)	12 (67 %)	25 (53 %)	16 (43 %)
Male	35 (44 %)	6 (33 %)	22 (47 %)	21 (57 %)
Age (years)	59 (15)	69 (9)	66 (10)	67 (9)
Body mass index (kg/m^2)	25.0 (3.6)	27.5 (5.3)	28.0 (4.3)	30.0 (5.8)

4. Discussion

The diagnosis of hip OA has historically relied on subjective clinical history, radiographic imaging, and/or physical examination, which are limited in terms of their reliance on patient self-report, time-consuming nature, and cannot be easily undertaken repeatedly due to radiation exposure. Our primary hypothesis was partially supported in that our diagnostic accuracies achieved a LR+ of more than 4.9, apart from the classification of KL3 hip OA. Human ethomics have a strong potential to revolutionise not only the diagnosis of OA but also in determining the severity of structural progression, paving the way for a novel, low-cost method of clinical diagnosis.

The diagnostic accuracy of the present human ethomics approach was greater than that using patient histories to diagnose the presence of any hip OA (LR+ range 2.06–7.80) (Metcalfe et al., 2019; Wright et al., 2021), using clinician-measured hip ROM (LR+ range 1.35–1.49) (Holla et al., 2012), and using a clinician-measured presence of a Trendelenburg sign (LR+1.83) (Youdas et al., 2010). Many of the current hip OA diagnostic studies have not considered the diagnostic performance of the test for determining structural severity, apart from Holla et al., (Holla et al., 2012), who reported that the LR+ values for hip ROM were between 1.35 (presence of osteophytes or joint space narrowing) to 1.49 (presence of osteophytes and joint space narrowing) when diagnosing different grades of hip OA. Although the human ethomics approach can increase the certainty of the presence of hip OA and its severity, it falls short in decreasing the post-test probability of a KL severity when the test yields a negative result. For example, if the pre-test probability of having a hip OA severity of KL4 was 50 %, a negative ethomics result (LR− of 0.56) would decrease the post-test probability of this severity to 36 %. However, this approach provides an excellent means of confirming a diagnosis, given the high specificity, as well as confidently excluding any OA, given the high sensitivity.

We anticipate that the ipsilateral hip flexion angle was the most influential diagnostic predictor and by a significant margin compared to the second most influential predictor, the ipsilateral neck flexion angle

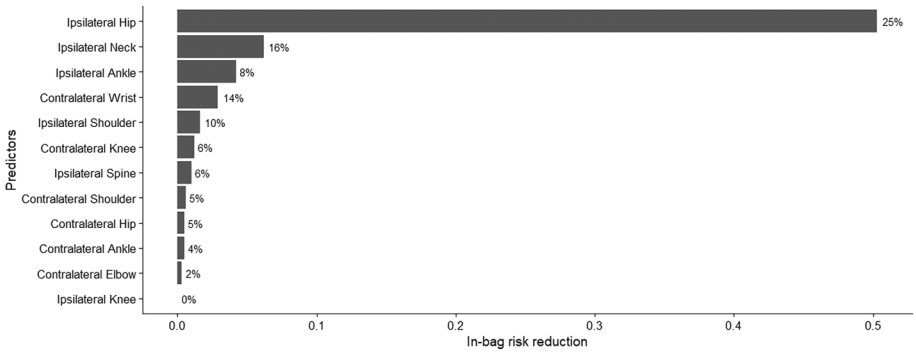

Fig. 1. Feature importance ranking of variables used in predicting hip OA severity. Percentage values indicate the proportion of times the feature was selected.

Table 2
Point estimate (95% bootstrapped confidence intervals) of the diagnostic performance metrics when predicting OA severity.

Statistic	KL0(ref) vs all	KL2 vs all (ref)	KL3 vs all (ref)	KL4 vs all (ref)
Accuracy	0.95 (0.92, 0.97)	0.9 (0.87, 0.93)	0.81 (0.76, 0.85)	0.85 (0.81, 0.88)
Odds ratio	633.97 (174.8, 1532.6)	23.98 (8.61, 58.54)	13.27 (7.13, 24.05)	19.03 (7.25, 46.51)
Negative likelihood ratio	0.07 (0.04, 0.11)	0.49 (0.24, 0.74)	0.38 (0.22, 0.55)	0.56 (0.33, 0.79)
Positive likelihood ratio	43.95 (14.9, 76.08)	10.81 (5.47, 22.78)	4.79 (3.2, 7.42)	10.2 (4.82, 27.43)
Negative predictive value	0.91 (0.88, 0.95)	0.95 (0.92, 0.97)	0.88 (0.84, 0.93)	0.88 (0.83, 0.92)
Positive predictive value	0.98 (0.95, 1)	0.52 (0.38, 0.71)	0.62 (0.53, 0.72)	0.69 (0.55, 0.88)
Sensitivity	0.93 (0.89, 0.96)	0.53 (0.28, 0.78)	0.68 (0.53, 0.81)	0.47 (0.22, 0.7)
Specificity	0.98 (0.94, 1)	0.94 (0.9, 0.98)	0.85 (0.78, 0.92)	0.94 (0.89, 0.99)

(Fig. 1). It is unlikely that our selected predictors were discriminating between the groups based on age differences. This is because there is uncertainty about whether walking kinematics changes significantly between 50 and 70 years old, which is the age range of participants in this study. While a previous meta-analysis has reported a reduction in hip sagittal plane ROM and peak extension angle in old compared to young adults, the studies compared older adults (average age: 70 years old) to younger adults (average age: 27 years old) (Boyer et al., 2017). More recent studies reported no differences in hip kinematics in adults between 50 and 70 years old (Moissenet et al., 2019; Rowe et al., 2021). Also, a previous study reported no significant difference in neck kinematics during walking between adults (average age: 27 years old) and older adults (average age: 70 years old) (Schmid et al., 2017).

The importance of neck kinematics during walking as a diagnostic predictor of hip OA was unexpected but suggests the importance of adopting a whole-body kinematic diagnostic approach. Previous studies have reported that biomechanical features of remote "normal" body regions could be just as important as local deficits when classifying neck pain disorders (Jiménez-Grande et al., 2021; Liew et al., 2020). Kinematic alterations in remote regions may compensate for local kinematic changes to preserve whole-body walking objectives, such stabilising the centre of mass trajectory (Tawy et al., 2017). Alternatively, the altered neck flexion angle could present a more cautious gait pattern, associated with increasing hip OA severity, that reflects a greater fall risk (Lin et al., 2015).

The ipsilateral knee flexion angle was the least influential predictor, which contradicts previous research (Meyer et al., 2015). Meyer et al., (Meyer et al., 2015) reported that the principal components relating to sagittal knee angle had a better classification accuracy for hip OA (area under the receiver operator curve [AUC] 0.91), than components relating to sagittal plane hip angle (AUC 0.765). Differences in the feature importance values of different variables could be attributed to the inclusion of participants with different levels of OA severity. Meyer

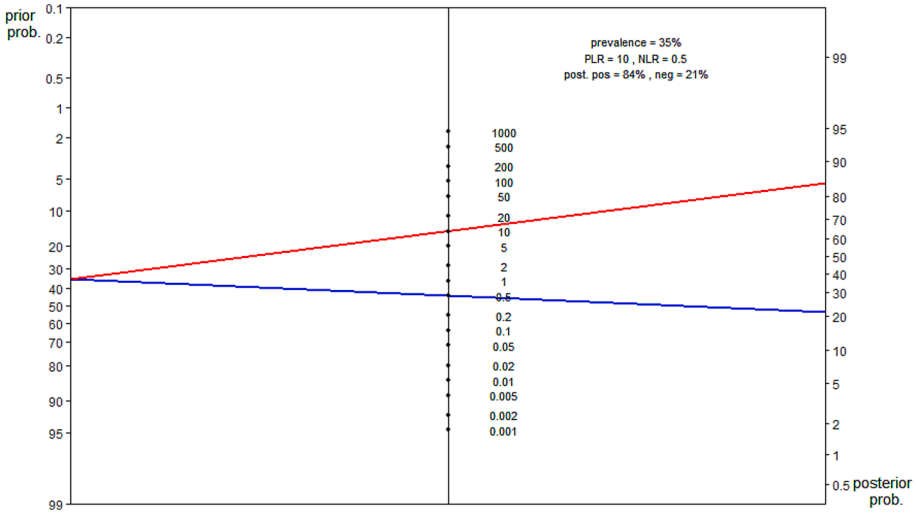

Fig. 2. Example of an application of the ethomics approach in adjusting the post-test probability of having OA of KL2 severity using a Fagan's nomogram.

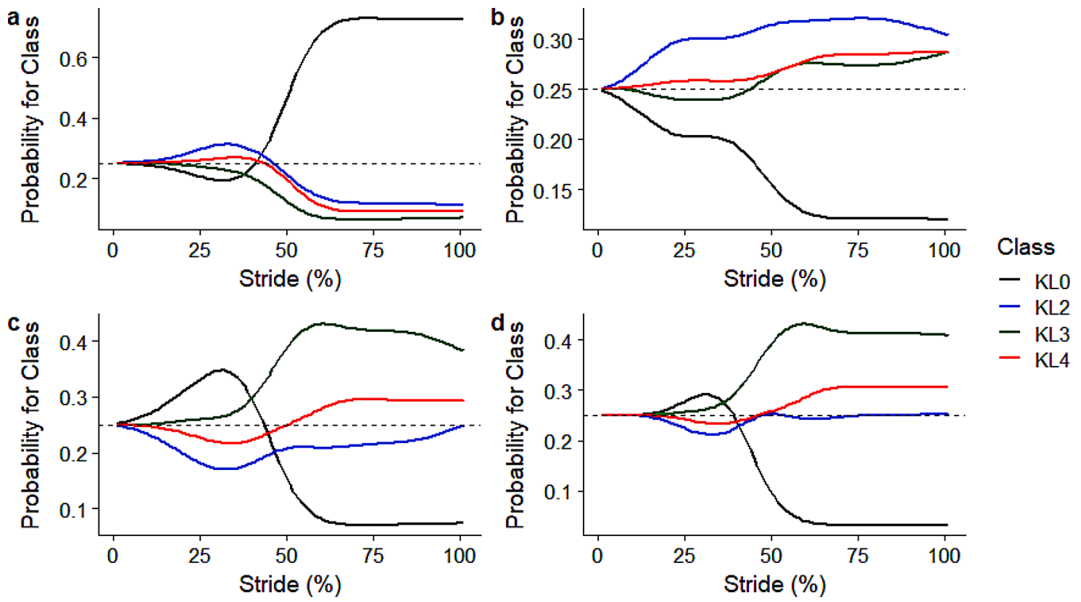

Fig. 3. Cumulative probability plots for the predictor of ipsilateral hip flexion–extension angle for four simulated "average" patients – i.e. patients with (a) no osteoarthritis, (b) osteoarthritis with KL2, (c) KL3, and (d) KL4 severity.

et al., (Meyer et al., 2015) included 15/18 people with hip OA with a Tönnis grading scale of 3 (graded between 0 [no OA] and 3 most severe), whilst the present study included OA participants with 17.6 % KL2, 46.1 % KL3, and 36.3 % KL4 severity. Given that a more severe structural hip OA resulted in greater knee flexion deficits (Eitzen et al., 2012), this may explain the greater prominence of knee kinematics in the previous study (Meyer et al., 2015).

A significant advantage of the present study is the use of a machine learning algorithm that not only achieves state-of-the-art prediction performance in multiple scientific domains (Brockhaus et al., 2020; Liew et al., 2020) but ensures transparency and model interpretability. Interpretability is ensured because the results can be interpreted similarly to logistic regression, and the change in the values of the predictors can be interpreted in terms of the original units (i.e., a 1° change in predictors). This is in contrast to other studies that transformed the biomechanical predictors into principal components (Meyer et al., 2015) and used more "black-box" algorithms (Laroche et al., 2014). In addition, using a functional data regression framework combined with model-based boosting ensured that feature engineering to extract discrete parameters from biomechanical waveforms was not required as a pre-processing step. Rather, the entire waveform can be used as individual predictors of a diagnostic model.

The present study is not without limitations. First, kinematic alterations between OA severities are present in many other activities of daily living, like sit-to-stand (Boswell et al., 2023). It may be that including kinematic alterations from a wider spectrum of motor tasks may further improve the diagnostic performance of OA severity. However, the range of tasks to be assessed will depend on the intended use case of the technology (e.g. in a busy clinic, self-assessment at home, or in a research lab). Second, only sagittal plane kinematics were used to develop a diagnostic model, due to the inaccuracies of the non-sagittal plane kinematics extracted using the PiG model. Improvement to the diagnostic performance may be possible with the use of 3D kinematics, given that prior studies have reported the diagnostic utility of non-sagittal plane hip ROM goniometric measurements (Metcalfe et al., 2019). However, the reliance on only sagittal plane kinematics may be clinically advantageous since 2D kinematics can be extracted from a single video camera (Boswell et al., 2023). This has the potential for diagnosis and monitoring of OA severity to occur remotely. Lastly, we built a diagnostic model using traditional motion capture technology. Presently, our model has the potential to be used for screening participants in hip OA research for study eligibility. Future work should investigate if kinematics gathered from markerless motion capture (Boswell et al., 2023) provide the same level of diagnostic accuracy as the present study.

5. Conclusions

Whole-body kinematics during gait was able to discriminate not only between people with and without hip OA, but also between OA severity. Human ethomics represents an ideal candidate for biomarkers of OA that could overcome many of the logistical challenges of traditional imaging and biochemical biomarkers. With the advent of smart technologies that can digitally quantify human ethomics in free-living environments, the door is open toward the development of novel diagnostic approaches that enable more rapid and early disease detection in OA.

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None.

CRediT authorship contribution statement

Bernard X.W. Liew: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Formal analysis, Conceptualization. **David Rugamer:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Methodology, Formal analysis. **Bradley S. Neal:** Writing – review & editing, Writing – original draft, Validation, Supervision. **Aleksandra Birn-Jeffery:** Writing – review & editing, Writing – original draft, Validation, Supervision, Methodology. **Qichang Mei:** Writing – review & editing, Writing – original draft, Validation, Supervision, Formal analysis. **Harry Roberts:** Writing – review & editing, Writing – original draft, Validation, Conceptualization. **Nelson Cortes:** Writing – review & editing, Writing – original draft, Validation, Supervision, 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.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jbiomech.2025.112724.

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