Original Article

Predicting Severe Knee Arthritis Based on Two Inertial Measurement Unit Sensors as a Dynamic Coordinate System Using Classical Machine Learning

Abstract

Background: Aging of societies in recent and upcoming years has made musculoskeletal disorders a significant challenge for healthcare system. Knee osteoarthritis (KOA) is a progressive musculoskeletal disorder that is typically diagnosed using radiographs. Considering the drawbacks of X-ray imaging, such as exposure to ionizing radiation, the need for a noninvasive, low-cost alternative method for diagnosing KOA is essential. The purpose of this study was to evaluate the ability of a wearable device to differentiate between healthy individuals and those with severe osteoarthritis (grade 4). **Methods:** The wearable device consisted of two inertial measurement unit (IMU) sensors, one on the lower leg and one on the thigh. One of the sensors is used as a dynamic coordinate system to improve the accuracy of the measurements. In this study, to discriminate between 1433 labeled IMU signals collected from 15 healthy individuals and 15 people with severe KOA aged over 45, new features were extracted and defined in dynamic coordinates. These features were employed in four different classifiers: (1) naive Bayes, (2) K-nearest neighbors (KNNs), (3) support vector machine, and (4) random forest. Each classifier was evaluated using the 10-fold cross-validation method (K = 10). The data were applied to these models, and based on their outputs, four performance metrics – accuracy, precision, sensitivity, and specificity – were calculated to assess the classification of these two groups using the mentioned software. **Results:** The evaluation of the selected classifiers involved calculating the four specified metrics and their average and variance values. The highest accuracy was achieved by KNN, with an accuracy of 93.71 ± 1.1 and a precision of 93 ± 1.31. **Conclusion:** The novel features based on the dynamic coordinate system, along with the success of the proposed KNN model, demonstrate the effectiveness of the proposed algorithm in diagnosing between signals received from healthy individuals and patients. The proposed algorithm outperforms existing methods in similar articles in sensitivity showing an improvement of 4% and at least. The main objective of this study is to investigate the feasibility of using a wearable device as an auxiliary tool in the diagnosis of arthritis. The reported results in this study are related to two groups of individuals with severe arthritis (grade 4), and there is a possibility of weaker results with the current method.

Keywords: *Classification, dynamic coordinates, feature extraction, inertial measurement unit, osteoarthritis*

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Submitted: 26-Mar-2024 **Revised:** 29-Aug-2024 **Accepted:** 14-Sep-2024 **Published:** 13-Mar-2025

Introduction

Osteoarthritis (OA) is a progressive condition where synovial fluid between the tibia1 and femoral articular surfaces gradually decreases, leading to increased friction, development of bony spurs, and reduction in the joint space.[1] OA impacts over 21 million individuals in the United States; 36% of Americans aged 70 or older exhibit some level of radiographic knee OA (KOA).[2] Given the aging population, diagnosing this disease poses a significant challenge for researchers. Inertial measurement unit (IMU), comprising accelerometer, gyroscope, and magnetometer, is a rapid, cost-effective, and noninvasive method for collecting kinematic data.[1] Considering the side effects of repeated exposure to ionizing radiation, X-ray device wear and tear, and lack of access to radiography facilities in remote areas, there is an increasing need

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Access this article online
Website: www.jmssjournal.net
DOI: 10.4103/jmss.jmss_18_24
Quick Response Code:

How to cite this article: Azizi E, Darbankhalesi M, Zare A, Rezaeian ZS, Kermani S. Predicting severe knee arthritis based on two inertial measurement unit sensors as a dynamic coordinate system using classical machine learning. J Med Signals Sens 2025;15:8.

for primary automated OA diagnosis by sensor variable. In recent years, machine learning-based approaches for disease diagnosis and progression have been employed based on IMU data.[3]

Temporal, frequency, and mechanical features of the disease, such as knee movement angle, joint rotation angle, and range of pelvic contraction, are valuable data to be discussed for diagnosis and prognosis of the disease using two sensors.[4-10] Tan *et al*.[4] tested two models, a double-leg model (four IMUs) and a single-leg model (two IMUs) to predict knee joint kinematics from wearable sensor data in people with KOA achieved RMSE (standard deviation [SD]) ranged from 7.04 (2.6) to 11.78 (6.04) compared to the motion capture system. Their study included 17 men with OA.[4] Challenges in previous results involve investigating IMU signal processing separately rather than concurrently in a unified reference or with limited datasets.

The aim of this study is to introduce a new method that analyzes leg and thigh movements using kinematic data. This method enables the automatic classification of motion data to distinguish between healthy and diseased knees. Additionally, it is designed for use in a simple embedded hardware system for real-time implementation.

This revision clarifies that the method focuses on distinguishing knee health based on motion data and can be applied to an embedded system. Let me know if further adjustments are needed.. The second aim of this study was to determine which of these four classifiers had better performance.

Methods

In this research, features based on dynamic coordinate systems in the time and frequency domains were extracted, and four classification algorithms, naive Bayes (NB), K-nearest neighbors (KNNs), random forest (RF), and support vector machine (SVM) were employed. The evaluation was performed using the 10-fold cross-validation method. The participants comprised 30 individuals, purposefully divided into two groups: 15 participants exhibiting no discernible health issues and 15 individuals were grappling with severe KOA. The mean age of the entire cohort stands at 56.88 years, with an SD of 9.78 years, reflecting a diverse age distribution. This intentional balance in participant selection ensures a comprehensive exploration of both health states within the study. The inclusion of 15 healthy individuals provides a robust baseline for comparison against the OA group, allowing for a nuanced investigation into the impact of this musculoskeletal condition on the variables of interest. The detailed characterization of this diverse and well-defined participant group forms the cornerstone of our study, enhancing the reliability and relevance of our findings as we delve into the intricacies of health-related phenomena. To acquire this dataset, wearable devices with two sensors were utilized. Figure 1 illustrates the placement of the widgets on individuals' legs, with two IMUs positioned on the shin and thigh equidistant from the knee joint. The acquired data include 9 indices from the two mentioned sensors. These indices comprise six parameters, precisely three linear acceleration and three angular velocity parameters in each direction we do. The data correspond to two groups: healthy individuals and those with severe arthritis (grade 4), requiring medical care and surgery according to medical diagnosis.

Figure 1: Placement of two inertial measurement unit sensors and the wearable device

To acquire data, individuals were instructed to take eight typical, 10-second steps without any assistive tools. The gold standard for differentiating KOA severity was based on X-ray images[5] and labeling was done based on the diagnosis of a physiotherapy specialist according to the Kellgren–Lawrence criterion.[2] Figure 2 illustrates the block diagram of the proposed algorithm. The first step was data acquisition that individuals were asked to take 8 steps in 10 s intervals normally. Diagnosis of severe arthritis was done using radiography as the gold standard. Demographic information, including health status, age, gender, height, and duration of symptoms, was collected. During preprocessing, the effect of gravity was removed by subtracting the DC value from the original signal, followed by segmenting the steps and applying the Resize technique to the raw data. After segmentation, each step was resized to 100 samples for uniformity. As shown in Figure 2, to ensure the stability of the extracted gait index, the first and last steps were removed. In the third step, nine features were extracted from both sensors, and the proposed features are listed in Table 1. In the next step, 4 models consist of naïve Bayes, KNN, SVM, and RF used for data classification. In the final stage, 4 criteria of accuracy, precision, sensitivity, and specificity were used to evaluate the results of the models.

In this study, the focus is on calculating mechanical indices related to the second sensor in the dynamic coordinate

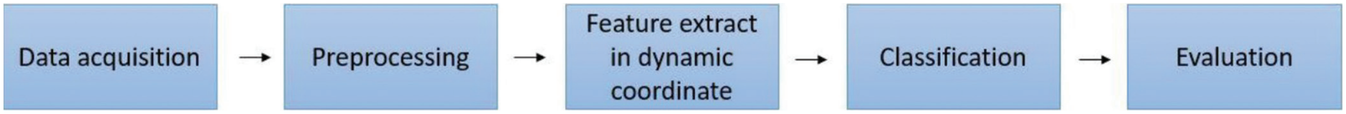

Figure 2: Block diagram of the proposed algorithm

system of the first sensor. For this purpose, direct kinematic calculations are required. Figure 3 illustrates the kinematic model from the head of the femur to the ankle, with reference coordinates denoted as 2. The positions of points A and B represent the locations of the two IMU sensors, and the position of B is determined using Eq. 1 (direct kinematics) based on the transformation (D-H) to the reference coordinate axis.

Eq. 1: $\begin{bmatrix} {}^{2}_{B}P \\ 1 \end{bmatrix} = {}^{2}_{3}T \begin{bmatrix} {}^{3}_{B}P \\ 1 \end{bmatrix}$

Eq. 2: ${}^{i+1}_{i}T = \begin{pmatrix} c\theta i & -s\theta ic\alpha i & s\theta is\alpha i & \alpha ic\theta i \\ s\theta i & c\theta ic\alpha i & -c\theta is\alpha i & \alpha is\theta i \\ 0 & s\alpha i & c\alpha i & di \\ 0 & 0 & 0 & 1 \end{pmatrix}$; C = cos, S = sin

$${}^{2}_{3}T = \begin{pmatrix} C\theta_3 & -S\theta_3 & 0 & \alpha_3 \\ S\theta_3 C\alpha_3 & C\theta_3 C\alpha_3 & -S\alpha_3 & -S\alpha_3 d_3 \\ S\theta_3 S\alpha_3 & C\theta_3 S\alpha_3 & C\alpha_3 & C\alpha_3 d_3 \\ 0 & 0 & 0 & 1 \end{pmatrix};$$

where: $\theta_3 = Integral(GzA - GzB) \quad \alpha_3 = 0;,$

$$\begin{bmatrix} P_{x2} \\ p_{y2} \\ p_{z2} \\ 1 \end{bmatrix} = \begin{pmatrix} C\theta_3 & -S\theta_3 & 0 & \alpha_3 \\ S\theta_3 & C\theta_3 & 0 & 0 \\ 0 & 0 & 1 & d_3 \\ 0 & 0 & 0 & 1 \end{pmatrix} \begin{bmatrix} P_{x3} \\ P_{y3} \\ P_{z3} \\ 1 \end{bmatrix};$$

In this context, ${}^{i}_{B}P$ and ${}^{i}_{i+1}T$ represent the position of point B in the ith coordinate system and the transformation matrix from the (i + 1)th to the ith coordinate system, as expressed by Eq. 2. Considering the spatial coordinate transformation from the Cartesian coordinate system 3-2, in Eq. 2, the value of i is set to 2. In addition, θ represents the knee joint angle at each moment, calculated by integrating the angular velocity difference obtained from points A and B. Consequently, point B is evaluated in the dynamic coordinate system 2. Thus, features related to both sensors are examined not separately but simultaneously in a shared dynamic coordinate system. With these analyses, 9 features were extracted from the IMU signal in the time and frequency domains for classification. Table 1 illustrates the proposed features along with those from other approaches.[6-11,13]

Considering the objective of this study, the performance of the proposed features for signal discrimination was evaluated using four standard classifiers through 10-fold cross-validation (K = 10). Test data were applied to the models, and by determining the outputs of the models and comparing them with the data labels, four indices of accuracy, precision, sensitivity, and specificity were calculated.

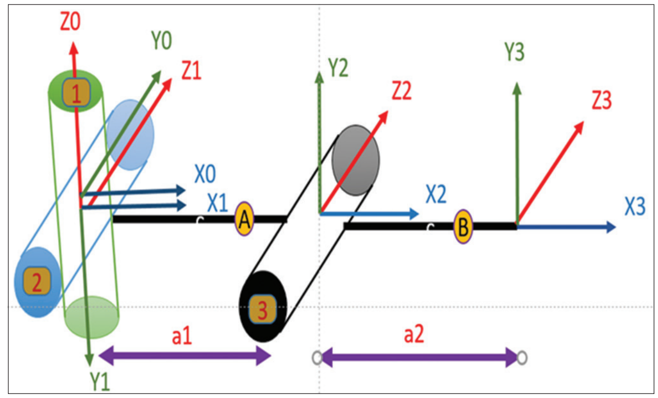

Figure 3: Kinematic model from the pelvis to the ankle

Table 1: The proposed features in our study and others

The standard features in other articles[6-12]	The proposed features
Time domain	Time domains
Mean±SD	Difference of accelerometer vectors from two sensors in X and Y axes
Variance	
Kurtosis	
Skewness	Difference of angular velocity vectors from two sensors about Z axes
RMS of the signal	
Pelvic flexion range	
Maximum knee flexion	Knee joint angle
Maximum knee rotation	Difference of positions of two sensors in X and Y axes
Knee flexion range	
Frequency domains	
Dominant frequency	Frequency domains
Spectral centroid	Transformations of the above features in the frequency domain
Edge frequency of the spectrum	
Motion-related	
Range of pelvic flexion motion	
Maximum knee flexion during gait	
Maximum knee rotation	
Range of knee flexion motion	

SD – Standard deviation; RMS – Root mean square

In the classification phase, signals from healthy individuals and patients were selected and applied to the NB, KNN, RF, and SVM classifiers. The four mentioned models were trained with the extracted eleven features. For proper training and testing of the classifiers, a 10-fold cross-validation method was employed. The SDs have been rounded to one decimal place.

Results

Table 2 indicates the results of the correlation coefficient and the significance level in the *t*-test for two groups of selected healthy individuals and patients, each consisting of 15 individuals, in one feature: body mass index (BMI). In the cells related to the Pearson correlation coefficient, these values indicate a linear relationship between the BMI of patients and healthy individuals. In the columns related to the significance level of the *t*-test, the Sig. (2-tailed) values are examined. The values of 0.952 in both cells of this column indicate the absence of a significant difference in BMI between the patient group and the healthy group. In fact, these high values mean that we cannot assume that the averages are different. Given the high significance level of over 95%, we cannot assume that the differences in BMI of individuals between the two groups (healthy and patient) are significant. To measure the degree of linear correlation between the two groups, the Pearson index is used, which according to the mentioned table, this coefficient is 89%.

Table 2: Correlation of age and body mass index in study groups

	BMI OA	BMI healthy
OA participants		
Pearson correlation coefficient	1	−0.898
Significance level of two-tailed *t*-test		0.952
Healthy participants		
Pearson correlation coefficient	−0.898	1
Significance level of two-tailed *t*-test	0.952	

BMI – Body mass index; OA – Osteoarthritis

According to Table 3, since the classifier output is of the screener type, the model's accuracies are more important than other parameters.

Eight hundred and fifty-nine signals from healthy individuals and 574 signals from patients were selected and applied to the four aforementioned models. The accuracies obtained from each are presented in Table 3. In all cases, the SD is <0.05%.

Figure 4 shows the raw data obtained from the sensor while walking in three coordinate directions.

We can see 3 parameters in 3 directions and resize all the signals in 100 samples.

As illustrated in Table 3, it is noteworthy that the most favorable results are associated with the angular position of the knee joint. Therefore, the average and variance of sensitivity, accuracy, precision, and specificity of this feature for each classifier are reported in Table 4.

According to the results in Table 4, model adaptation to the data was the highest KNN that gradually reduced to the lowest level of accuracy in SVM, NB, and RF, respectively. Considering the classifier deployment results, the KNN classifier has the highest accuracy at 93.71%, followed by the SVM classifier at 93.17%, indicating that KNN and SVM classifiers can be suitable models for diagnosing patients using IMU signals.

In Table 5, the name of the reference, number of patients, extracted features, type of classifier, and evaluation of results are provided. This table shows that in some of these studies, there was not enough data or other joint diseases were studied.

Table 3: Average accuracies of knee angle for 10-fold cross-validation

Feature	Classifier			
	NB	KNN	SVM	RF
Accx2-Accx1	95.63±1.19	91.73±0.87	88.62±2.01	69.44±1.2
Accy2-Accy1	89.13±0.92	91.69±0.9	87.89±1.41	71.98±1.48
Gz2-Gz1	84.46±1.4	92.53±1.02	86.53±1.5	70.10±2.2
Knee angle	92.74±2.66	93.71±1.1	93.17±1.04	73.22±1.21
Px2-Px1	88.66±2.12	92.99±0.92	91.99±0.92	70.76±1.02
Py2-Py1	91.06±1.87	92.96±1.17	92.93±1.4	69.90±1.17
F-Px2-Px1	87.33±0.93	88.54±1.43	88.22±1.72	67.76±1.3
F-Py2-Py1	90.09±1.64	89.20±1.51	87.52±1.38	69.09±0.96
F-knee angle	92.80±1.7	92.20±1.96	89.03±1.45	70.89±1.26

NB – Naive Bayes; KNN – K-nearest neighbors; SVM – Support vector machine; RF – Random forest

Table 4: Average results of knee angle for 10-fold cross-validation

Row	Classifier	Accuracy (%)	Precision (%)	Specificity (%)	Sensitivity (%)
1	NB	92.74±2.66	92.91±2.04	93.87±1.98	91.44±2.1
2	KNN	93.71±1.1	93±1.31	93.82±0.98	93.57±1.08
3	RF	73.22±1.21	63.88±1.4	70.44±1.22	76.86±0.99
4	SVM	93.17±1.04	93.50±1.02	94.33±0.98	91.85±1.13

NB – Naive Bayes; KNN – K-nearest neighbors; SVM – Support vector machine; RF – Random forest

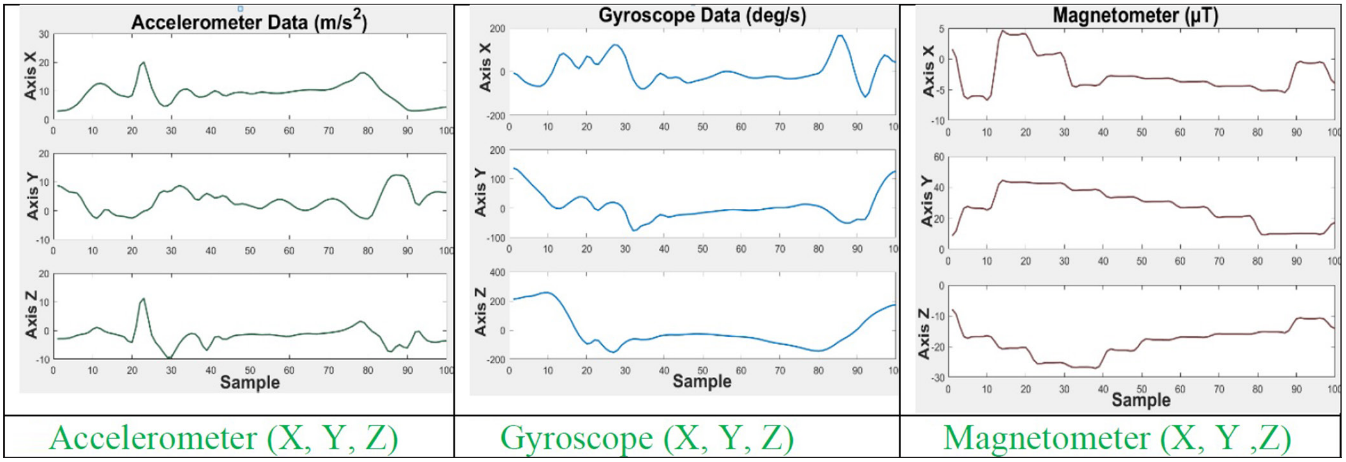

Figure 4: The raw signal obtained from the inertial measurement unit while walking in three coordinate directions (X, Y, and Z) during one step

Table 5: Summary of conducted studies and previous researches

Reference	Participants number	Feature extracted	Classifiers	Evaluation results
Azizi *et al*. (present study)	30	Accx2-Accx1 Accy2-Accy1 Gz2-Gz1 Knee angle Px2-Px1 Py2-Py1 F-Px2-Px1 F-Py2-Py1 F-Knee angle	NB KNN RF SVM	Accuracy: 93.71%±1.1 Precision: 93.50%±1.02
Wafaa Salem Almuhammadi *et al*.[15]	53	Step length Time of a length swing and stance time	SVM DT	Precision: 86/79%
Kermani s *et al*.[14]	20	Acceleration in 3 directions	Wavelet DTW	Accuracy: 94% and 95%
Tan JS *et al*.[4]	17	Knee angle	LSTM CNN	Pearson correlation coefficient: 85%
Rezvan Kianifar *et al*.[10]	19	RMS value of signal STD Variance Mean Skewness Kurtosis Range of signal Min	SVM	Accuracy: 95%
Fedor Myagkov *et al*.[11]	20	Mean-sum of squares of values FFT for parameters of linear Acceleration Angular velocity Magnetic field	ET RF DT KNN SVM	Accuracy: 92% F1-score: 94% Precision: 96%

NB – Naive Bayes; KNN – K-nearest neighbors; SVM – Support vector machine; RF – Random forest; RMS – Root mean square; DT – Decision tree; DTW – Dynamic time warping; FFT – Fast fourier transform; ET – Extra trees; LSTM – Long short-term memory; CNN – Convolutional neural network; STD – Standard deviation

Discussion

The use of IMU (with the technique of dynamic coordinate system) as a noninvasive, cost-effective, and fast method for detecting movement disorders and diseases, particularly KOA, has been explored in this study. A sensor was considered a dynamic coordinate system reference, and changes in mechanical indices of the second sensor in this system were recorded. In this study, an attempt was made to introduce a new method for detecting signals from normal and diseased individuals. According to the presented results, using 9 proposed features based on the dynamic coordinate system has significantly improved the outcomes. In our literature review, Myagkov *et al*.[11] achieved accuracy and precision of 92% and 94%, respectively, in various tasks related to physiotherapy movements using two sensors. However, this study included 30 participants, both men and women, with and without OA. In this research, in its best case, accuracy and precision reached 93.71% ± 1.1% and 93% ± 1.31%, respectively. The proposed algorithm outperforms existing methods in similar articles. Furthermore, Kermani *et al*.[14] used a tri-axial accelerometer to differentiate the stance and swing phases in a study involving 20 healthy individuals and 20 individuals with anterior cruciate ligament ruptures. Accuracy rates for these two phases were 94% and 95%, respectively.[9] However, in this study, both the number of patients and healthy individuals decreased to 15, indicating a smaller study population. In contrast to the previous study, which was limited to linear acceleration parameters, this research also encompassed angular velocity around three axes. Consequently, composite features such as joint angles at each moment and spatial position were utilized to enrich the dataset. The accuracy rate for this study reached 93.71%. In another study,[15] a classification task was undertaken on 53 individuals with knee and hip OA, utilizing a waist-mounted accelerometer sensor. The researchers extracted temporal and spatial features using classic classifiers, achieving an accuracy of 86.79% with decision tree classification and 83.57% with SVM in the best-case scenario. Similar to the previous case, in our study, in addition to linear acceleration parameters, angular velocity and its associated parameters were also employed, resulting in improved accuracy in the optimal conditions. Furthermore, our study distinguishes between healthy individuals and those with severe OA. In another study, Xia *et al*.[16] conducted research on 36 individuals with arthritis and 14 healthy individuals using classic classifiers such as SVM, decision tree, and RF to differentiate healthy individuals from those with knee arthritis (grade 2 and above). As a result, in the best-case scenario using data from 3 sensors, the sensitivity reached 86%. In our study, this parameter reached 93.57% using 2 sensors in two groups of 15 individuals, totaling 30 people. Another study[17] involving 27 individuals with knee arthritis and 18 healthy individuals, using a single sensor placed on the lateral thigh, achieved an accuracy of 95%. Statistical analysis of the participants in this study revealed that at a 5% significance level, the two groups were statistically different. However, in our study, these two groups were not different at the same 5% significance level, and the comparison between the two groups was statistically significant. Ultimately, in the best-case scenario, the two groups were differentiated with an accuracy of 93.71%. Given that the goal of this study was to explore the feasibility of predicting arthritis using the mentioned device and considering that in this study, the individuals under investigation only included those with severe arthritis (grade 4), this may be justifiable for the reported results. Therefore, it is possible that in a study on milder forms of KOA, the results obtained with the mentioned method may decrease. Table 3 indicates that the proposed features have enhanced the results, making them practical for diagnosing these two groups of individuals. Regarding accuracy, the results obtained from the KNN classifier are superior to all reported results in Table 4.

Conclusion

The goal of this study was to diagnose individuals with severe arthritis (grade 4) from healthy individuals. In the following study, data related to arthritis grades 2 and 3 and adding these categories to the classifiers will be applied to make this method more practical.

The introduced features have the necessary capability to detect and differentiate between individuals with severe arthritis and healthy individuals. The best model was obtained with the mentioned KNN classifier features. To improve this method, the use of data from individuals with arthritis in grades 2 and 3, and increasing the number of classes, will be considered in future studies.

Financial support and sponsorship

Nil.

Conflicts of interest

There are no conflicts of interest.

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