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Anomaly detection in vibroarthrographic signals using handcrafted signal features and one-class methods

Abstract

Knee osteoarthritis (OA) alters joint mechanics and may modify vibroarthrographic (VAG) signals generated during movement. This study evaluates whether OA-related changes can be detected as anomalies relative to a reference distribution learned exclusively from healthy participants, without using OA data during model training or threshold selection. VAG signals were obtained from 97 participants, including 48 healthy controls (HC) and 49 patients with clinically and radiologically confirmed knee OA. Signals recorded with a contact microphone positioned on the patella during closed-kinetic-chain (CKC) movement were segmented into cycles and represented by eight handcrafted time-, amplitude-, and frequency-domain features. Four one-class anomaly detection methods were compared: Mahalanobis distance, One-Class Support Vector Machine, robust Euclidean distance, and Isolation Forest. Performance was assessed over 50 participant-level random splits at the cycle, joint, and patient levels. Mahalanobis distance achieved the highest ROC AUC at all aggregation levels, reaching 0.703 ± 0.049 for cycles, 0.731 ± 0.059 for joints, and 0.729 ± 0.075 for patients. Threshold-based evaluation using percentiles derived solely from healthy validation data yielded high specificity but limited sensitivity; the best balanced accuracy at the patient level was 0.627 ± 0.062 with the P90 threshold, with sensitivity of 0.386 ± 0.202 and specificity of 0.868 ± 0.164 . These findings demonstrate the feasibility of modelling knee OA as a deviation from a multidimensional healthy VAG pattern and support one-class analysis as a complementary framework for non-invasive functional assessment, while indicating that further development is required to improve sensitivity.

1. INTRODUCTION

Osteoarthritis (OA) is one of the leading causes of chronic pain and reduced mobility, and the knee joint is the most commonly affected site (Bryliński et al., 2025; Liu et al., 2025; Zhang et al., 2026). The Global Burden of Disease analysis showed that in 2020, approximately 595 million people were living with OA, while the number of knee OA cases is projected to increase by about 75% by 2050 (Steinmetz et al., 2023). More recent estimates for knee osteoarthritis indicate approximately 374.7 million cases in 2021, with a further projected increase in the disease burden in the coming decades (Chen et al., 2025). The growing number of patients, the chronic nature of the degenerative process, and its impact on mobility and function justify the development of methods that enable objective assessment of the joint at a stage before advanced functional impairment (Collins et al., 2026; Dell’Isola et al., 2025; Peng et al., 2025). Of particular importance are noninvasive, reproducible solutions that can be applied without extensive diagnostic infrastructure, and that can support patient selection for further testing, monitoring of changes over time, and assessment of response to conservative management (De Tocqueville et al., 2021; Karpiński, 2022; Karpiński & Syta, 2025).

The diagnosis of knee osteoarthritis (OA) is based on integrating the clinical picture with an assessment of structural changes, although the relationship among symptoms, physical examination findings, and radiographic findings is not fully understood (Parsons et al., 2018). Radiography remains the primary method for quantitatively assessing the severity of structural changes, particularly using the Kellgren-Lawrence scale; however, the benefit of obtaining an X-ray depends on the clinical context, and radiographic grading itself is subject to inter- and intra-observer variability (Köse et al., 2018; Wang et al., 2020). Magnetic resonance

imaging provides significantly more detailed information about the cartilage, subchondral bone, menisci, and other joint structures; however, its cost, examination time, and equipment requirements limit its usefulness for frequent, population-based monitoring. Therefore, there is significant potential for complementary functional biomarkers that do not replace imaging but instead describe the joint's dynamic properties during actual movement.

Advances in artificial intelligence have significantly expanded the capabilities of automated medical data analysis (Dołęga-Kozierowski et al., 2023; Kwiatkowski et al., 2023), including analysis of OA-related data (Belton et al., 2025; Mohammadi et al., 2024). In radiography, deep convolutional neural networks have been used to detect OA and automatically grade lesions according to the Kellgren-Lawrence scale (Chen et al., 2019; Norman et al., 2019; Thomas et al., 2020; Tiulpin et al., 2018). In large image datasets, the ability to achieve agreement with specialist assessments and high reproducibility of automatic grading has been demonstrated (Swiecicki et al., 2021). At the same time, recent cross-centre validation studies show that high internal validity does not eliminate domain shift and a decline in quality when applying the model to a population from another centre, underscoring the importance of controlling for data leakage, patient-level splitting, and external validation (Alkhatatbeh et al., 2026). Machine learning algorithms are also used to predict OA progression from radiographs and clinical data (Tiulpin et al., 2019), to predict the risk of joint replacement from magnetic resonance imaging (Tolpadi et al., 2020), to assess progression on MRI (Schiratti et al., 2021), and to analyse radiomic features of the subchondral bone (Hirvasniemi et al., 2021). This approach confirms the potential of AI to extract quantitative OA biomarkers, but it remains largely dependent on well-defined diagnostic labels and a sufficiently large number of examples for each disease stage.

At the same time, digital biomarkers describing musculoskeletal function are being developed. Inertial sensors, measurement insoles, and portable gait analysis systems enable the quantitative assessment of parameters that previously required laboratory-based motion analysis systems. Insoles equipped with distributed pressure sensors have enabled the identification of gait patterns associated with knee arthropathy using machine learning (Wipperman et al., 2024), while inertial measurements allow for the objectification of gait characteristics in patients with OA (Boekesteijn et al., 2021) and provide information that is partially independent of traditional radiological parameters and patient-reported outcomes (Van Helvoort et al., 2021). Methods have also been developed to estimate knee adduction torque using IMU data (Iwama et al., 2021) and machine learning models that utilise signals from wearable sensors (Stetter et al., 2020). Biomechanical studies indicate that OA is associated with measurable disturbances in gait patterns and changes in joint dynamic loading (Kobsar et al., 2019; Marriott et al., 2019). A common feature of these approaches is a shift away from a purely static morphological picture toward a digital characterisation of joint behaviour during movement.

This group of methods includes vibroarthrography (VAG), in which the vibrations and sounds generated during joint movement are recorded, and their temporal, amplitude, and frequency characteristics are analysed. The physical basis of this concept is the assumption that the interaction between articular surfaces and periarticular tissues generates mechanical signals that depend on contact conditions and movement dynamics. Previous studies of acoustic emission have indicated that the signal generated by the knee may contain information about processes related to ageing and joint degeneration (Shark et al., 2011), and VAG measurements in patients with arthropathy have shown differences from those in healthy individuals within specific frequency ranges (Tanaka & Hoshiyama, 2012). Changes in the patellofemoral cartilage have been linked to modifications in the amplitude and frequency composition of the vibroacoustic signal (Bączkiewicz & Majorczyk, 2016). More recent studies have confirmed correlations among joint acoustic emission, kinematic instability, and radiographic features of OA (Nevalainen et al., 2021), and acoustic emission analysis has also been used to quantitatively assess joint surface condition (Sawaryn et al., 2021). These results justify considering VAG as a candidate for a functional digital biomarker of joint mechanics, although the direction of change in individual parameters may not be universal and may depend on the movement protocol, sensor placement, load, and signal-processing method.

To date, automated VAG analysis has focused primarily on identifying features that enable the differentiation of defined diagnostic groups. Methods used included feature selection and SVM or Random Forest classifiers (Nalband et al., 2016), entropy and envelope measures to characterise signal irregularities (Wu et al., 2016), multiclass classification of knee pathology (Kręcis & Bączkiewicz, 2018), normalised frequency features for OA identification (Befrui et al., 2018), and CEEMDAN decomposition combined with entropy descriptors and classification (Nalband et al., 2018). Multi-class spectral representations of VAG signals (Łysiak et al., 2020) and a concept for telemedical joint assessment using these signals (Athavale & Krishnan, 2020) were also developed. Recent studies continue in this direction: in 2025, advanced signal

processing, self-organising maps, and k-means clustering were applied to analyse VAG in OA (Kumar et al., 2025), and in 2026, a transformation of the vibroarthrogram from the time domain to the joint angle domain was proposed to better correlate signal events with the phase of motion (Łysiak et al., 2026).

Despite significant methodological progress, the dominant framework for VAG analysis remains classification-oriented: during training, the model is presented with examples representing health and one or more defined pathologies, and its task is to determine the boundary between these categories. This formulation is natural, but it ties the model's characteristics to the available disease classes, their definitions, and the training set's representativeness. This is particularly significant in OA, which is not a homogeneous mechanical condition: a comparable clinical or radiological label may encompass varying degrees of involvement of specific structures, different movement strategies, and varying symptom expression. Importantly, the inclusion of unsupervised clustering methods in VAG analysis does not bridge this gap. For example, a 2025 study used SOM and k-means to uncover the structure of OA data but still analysed patterns derived from a pathological population (Kumar et al., 2025). This is not equivalent to constructing a model whose sole training data consists of the physiological variability of a healthy signal.

One-class anomaly detection offers an alternative formulation of the problem. Instead of estimating the boundary between two predefined populations, the model describes the region of feature space occupied by reference observations and assigns a new signal a degree of deviation from the learned normal pattern. Modern one-class methods expand on this idea by learning compact representations of the normal class (Perera & Patel, 2019), modelling multilayer representations relative to a data centre that does not contain anomalies (Massoli et al., 2022), or directly estimating the region of minimum volume encompassing the distribution of the reference class (Maziarka et al., 2021). The validity of this paradigm for biosignals is also demonstrated by recent electrocardiographic studies, in which anomalies were identified in a representation learned largely unsupervised, while simultaneously emphasising the importance of interpretability and inter-individual variability (Kapsecker et al., 2025). In the context of biomedical signals, this approach is particularly interesting when the reference state can be characterised more consistently than the full spectrum of potential pathological deviations.

To the best of our knowledge, the available literature lacks well-validated studies in which the detection of OA based on VAG would be formulated as a one-class anomaly detection problem: the reference distribution would be estimated exclusively from signals of healthy individuals; OA data would not be used either to fit the normal distribution or to determine the decision boundary, and their role would be limited to an independent assessment of the detector's ability to identify atypical observations. The novelty of the present study lies in this strict healthy-only formulation. This is a shortcoming distinct from the problem of selecting another classifier or a more complex VAG descriptor. It concerns the very definition of the diagnostic task. In supervised classification, the question is which of the known classes a signal belongs to; in anomaly detection, however, the question concerns whether the observed mechanical-acoustic pattern remains consistent with the multidimensional range of variability characteristic of a healthy joint. Previous work on VAG provides ample evidence of features that distinguish normal from pathological states (Befrui et al., 2018; Kręcis & Bączkiewicz, 2018; Łysiak et al., 2020; Machrowska et al., 2024, 2025a, 2025b; Nalband et al., 2016; Wu et al., 2016), while the literature on single-class classification offers methods for describing a reference distribution without needing to model all possible types of deviations (Massoli et al., 2022; Maziarka et al., 2021; Perera & Patel, 2019). The combination of these two lines of research constitutes the fundamental motivation for the proposed approach.

VAG analysis is interdisciplinary, combining biomechanics and orthopaedics, acoustics and vibroacoustics, biomedical engineering, and machine learning. These fields enable an accurate description of the conditions governing joint motion, the mechanisms underlying vibration generation, methods for acquiring and analysing biosignals, and the multidimensional relationships among their characteristics. In VAG, information about the joint's condition may be distributed across parameters such as energy, impulsivity, irregularity, and frequency content; therefore, clinically significant changes may result from the configuration of several features rather than from a single parameter. For this reason, interpretable multidimensional modelling offers a valuable alternative to one-dimensional analyses and to complex models that require large datasets.

The aim of this study is therefore to assess whether changes associated with knee osteoarthritis (OA) can be detected as anomalies when compared to the distribution of VAG signal characteristics in healthy individuals. In accordance with the study design, the reference model is created exclusively from data from healthy participants, while signals from patients with OA are excluded during model training and used only for evaluation. Each movement cycle is characterised by eight interpretable features: mean absolute amplitude,

RMS, kurtosis, crest factor, frequency of zero crossings, normalised dominant frequency, spectral centroid, and spectral entropy. In this representation, four methods for determining the anomaly score are compared: Mahalanobis distance, One-Class SVM, Isolation Forest, and robust Euclidean distance. Validation is performed at the patient level, and decision thresholds can be determined solely from the distribution of results in the healthy validation group, without using information derived from OA. This assumption distinguishes the proposed solution from the classical HC-OA classification and allows for an assessment of the extent to which pathology can be recognised as a deviation from an empirically defined physiological pattern.

2. MATERIALS AND METHODS

This study employed a multi-stage procedure for analysing vibroarthrographic signals, including signal acquisition and preprocessing, extraction of interpretable features, construction of a reference model based on data from healthy individuals, and assessment of the deviation of observations from the learned physiological pattern. The methodology was designed in accordance with the one-class anomaly detection paradigm, such that data from patients with knee osteoarthritis were not used for feature standardisation, detector training, or decision threshold determination, but were used exclusively in the final effectiveness evaluation stage. The general flow of the analytical procedure used is shown in Figure 1.

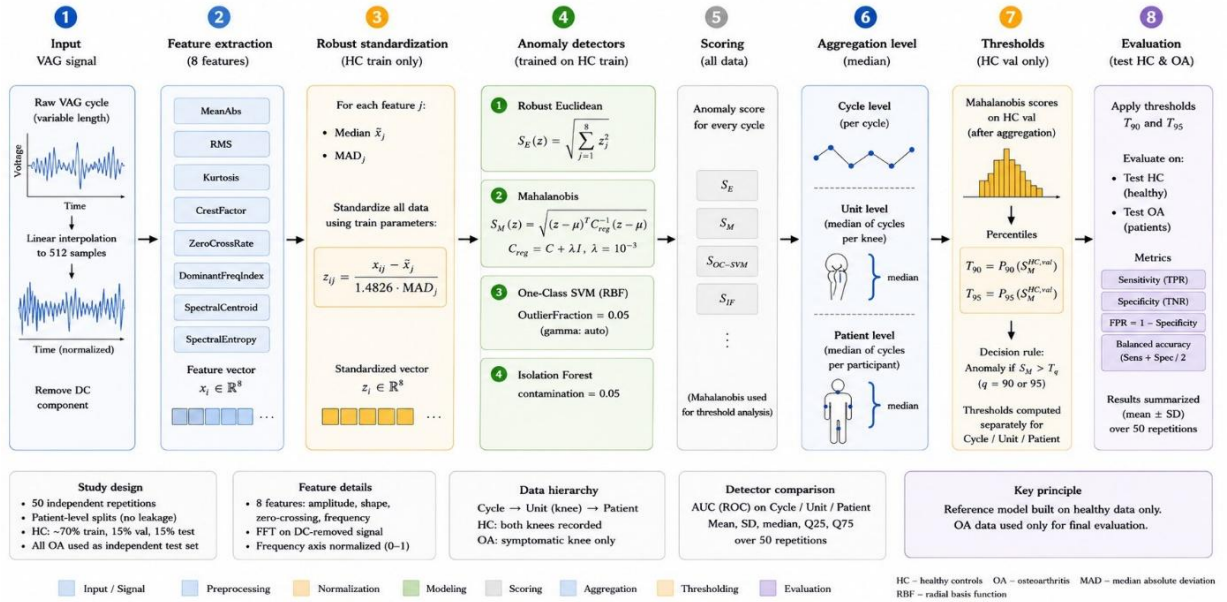


Fig. 1. Schematic diagram of the VAG signal processing and one-class anomaly detection procedure, including feature extraction, robust standardisation, modelling based on data from healthy individuals, aggregation of results, determination of decision thresholds, and final evaluation using HC and OA data

Figure 1 illustrates the successive stages of the developed procedure, from normalising VAG cycle lengths and determining an eight-dimensional feature vector, through robust standardisation and the application of four anomaly detection methods, to aggregating results at the cycle, joint, and participant levels. The diagram highlights the key premise of the study: the reference model and decision thresholds are determined exclusively from data on healthy individuals, while OA data are independent of the training process and used only during the final evaluation of the detectors.

1.1. Dataset, measurement setup, and study protocol

This study utilised data from the same experimental set of vibroarthrographic (VAG) signals, which had previously been described in detail and used in studies on the nonlinear analysis of acoustic signals from the knee joint and their decomposition using Variational Mode Decomposition (Karpiński et al., 2026; Karpiński & Syta, 2026). The dataset was created as part of research conducted in collaboration between the Lublin University of Technology and clinical departments in Lublin and Łęczna. The study was conducted in

accordance with the principles of good clinical practice, following approval by the Bioethics Committee of the Medical University of Lublin (KE-0254/261/2019).

The full dataset comprised 97 participants, including 48 healthy controls (HC) and 49 patients with clinically and radiologically confirmed knee osteoarthritis (OA) who were eligible for surgical treatment. In the control group, both knee joints were examined, with the exception of one participant for whom a signal was recorded from only one limb. This means that a total of 95 knee joints were examined in the HC group. In the OA group, only the symptomatic joint (which was scheduled for surgical treatment and subsequently evaluated intraoperatively) was analysed, for a total of 49 knee joints. Thus, the dataset comprised recordings from 144 knee joints. In the OA group, the VAG examination was performed the day before the scheduled procedure, and the symptomatic knee joint to be treated surgically was analysed. In the control group, signals were recorded from both knee joints, except for one participant.

The demographic and clinical characteristics of the study groups were as follows. The HC group comprised 48 participants (16 males and 32 females), with a mean age of 27.33 ± 10.58 years, height of 1.71 ± 0.08 m, body weight of 69.38 ± 15.11 kg, BMI of 22.94 ± 4.96 , and Lysholm score of 98.15 ± 4.56 . The OA group comprised 49 participants (25 males and 24 females), with a mean age of 54.88 ± 14.63 years, height of 1.70 ± 0.09 m, body weight of 87.53 ± 13.69 kg, BMI of 30.32 ± 4.69 , and Lysholm score of 46.33 ± 17.79 .

The recording was performed using a proprietary, portable measurement system that enabled simultaneous acquisition of vibroacoustic signals and angular position data for the knee joint. The system included an Arduino Mega2560 R3 microcontroller, a CM01B piezoelectric contact microphone, and an EMS22A50-D28-LT6 absolute rotary encoder integrated into the Breg T-Scope Knee brace. The encoder enabled continuous measurement of the joint's angular position during successive flexion and extension cycles, allowing the VAG signal to be synchronised with the movement phase. To minimise electrical interference, galvanic isolation was applied to the USB interface, and the system was powered by an 11.1 V lithium-ion battery. The recorded data were saved at a sampling rate of 1400 Hz and a resolution of 10 bits. A detailed description of the measurement system is presented in (Karpiński et al., 2024).

In this analysis, we used a signal recorded with a contact microphone positioned centrally on the patella and secured to the skin with double-sided tape. This mounting ensured stable contact between the sensor and the skin and minimised sensor displacement during movement. The location on the patella allowed for the recording of vibrations primarily associated with the mechanics of the patellofemoral joint. The proximity to bony structures facilitated the transmission of vibrations generated within the joint and limited their attenuation by soft tissues.

This study utilised recordings made during movement in a closed kinetic chain (CKC) (Karpiński et al., 2019; Machrowska et al., 2019). The test began with the participant seated in a chair, with the knee flexed to approximately 90° . The participant then performed a controlled transition to a standing position, corresponding to knee extension to approximately 0° , after which they returned to the sitting position and re-flexed the knee to approximately 90° . The feet remained in contact with the ground at all times, while the upper limbs were kept crossed over the chest to minimise the impact of their movements on the recorded signal. One full cycle of movement lasted approximately 2 s, and 10 consecutive repetitions were recorded for each participant. Simultaneous recording of the vibroacoustic signal from the patellar region and the joint's angular position enabled correlation of changes in signal characteristics with the successive phases of loaded knee movement.

1.2. Signal processing

Due to natural inter-individual differences in movement execution time, individual cycles contained different numbers of samples. To standardise the signal representation, each cycle was linearly interpolated to 512 samples on a normalised time axis spanning from the beginning to the end of the cycle.

For each cycle, eight features describing the amplitude-related, statistical, and frequency-domain properties of the signal were extracted: mean absolute amplitude (MeanAbs), root mean square (RMS), kurtosis (Kurtosis), crest factor (CrestFactor), zero-crossing rate (ZeroCrossRate), dominant frequency index (DominantFreqIndex), spectral centroid (SpectralCentroid), and spectral entropy (SpectralEntropy). Parameters derived from these domains are widely used to quantitatively characterise acoustic and vibration signals, including VAG signals (Ambrożkiewicz et al., 2023; Jedliński et al., 2022; Rangayyan & Wu, 2008; Wu et al., 2010).

Frequency-domain features were calculated after removing the DC component, based on the power spectrum obtained via the fast Fourier transform (FFT). The locations of the spectral components were

expressed on a normalised, dimensionless frequency axis ranging from 0 to 1. The resulting eight-dimensional feature vector served as the representation of each cycle used in subsequent analyses.

1.3. Reference model of healthy signals

The problem was formulated as a one-class anomaly detection task, in which the reference model was constructed exclusively from data obtained from healthy controls (HC). Data from patients with OA were not used for model training, estimation of normalisation parameters, or determination of decision thresholds (Chandola et al., 2009).

To assess the stability of the proposed method, 50 independent repetitions of a random split of the HC dataset were performed. The partitioning was conducted at the participant level, ensuring that all cycles originating from a given participant were assigned exclusively to a single subset. In each repetition, 70% of HC participants were used to construct the reference model, 15% were allocated to validation, and the remaining 15% were used as an independent HC test set. All OA cases were used exclusively as an independent test set.

Before constructing the reference model, the features were subjected to robust standardisation using the median and the median absolute deviation (MAD), with both parameters estimated exclusively from the HC training set (Rousseeuw & Hubert, 2018):

$$z_{ij} = \frac{x_{ij} - \tilde{x}_j}{1.4826 \text{ MAD}_j} \quad (1)$$

where x_{ij} denotes the value of the j -th feature for the i -th cycle, while $\tilde{x}_j$ and MAD_j denote the median and median absolute deviation, respectively, of that feature in the HC training set. The same transformation parameters were subsequently applied to the HC validation set, HC test set, and OA data.

1.4. Anomaly detection methods

Four anomaly detection methods were compared: robust Euclidean distance (Robust Euclidean), Mahalanobis distance, One-Class Support Vector Machine (OC-SVM), and Isolation Forest. All detectors were constructed exclusively using the HC training data.

For the robust Euclidean distance method, the anomaly score was defined as the norm of the robustly standardised feature vector:

$$S_E(z) = \sqrt{\sum_{j=1}^p z_j^2} \quad (2)$$

where $p = 8$ denotes the number of analysed features.

In the case of Mahalanobis distances, the relationships between individual features were also taken into account. Based on the standardised HC training data, the mean vector μ_{HC} and the covariance matrix C were estimated. To improve numerical stability, the covariance matrix was regularized as follows:

$$C_{reg} = C + \lambda I \quad (3)$$

Where $\lambda = 10^{-3}$.

The anomaly result for the observation was then calculated as:

$$S_M(z) = \sqrt{(z - \mu_{HC})^T C_{reg}^{-1} (z - \mu_{HC})} \quad (4)$$

For OC-SVM, a radial basis function (RBF) kernel was used, with automatic kernel scale selection and an outlier fraction of 0.05 (Schölkopf et al., 2001). For Isolation Forest, the contamination parameter was likewise set to 0.05 (Liu et al., 2008).

Among the methods compared, the Mahalanobis distance was selected as the primary detector for subsequent threshold-based analysis, while the remaining methods served as comparators.

1.5. Performance evaluation

The performance of the methods was evaluated at three levels of the data hierarchy: individual cycle (cycle), examined joint (joint), and participant (participant). At the cycle level, the anomaly score of each individual cycle was used. At the joint and participant levels, cycle-level scores were aggregated using the median for each joint and participant examined, respectively. Bilateral recordings occurred only in the healthy group, and both knees from the same participant were always assigned to the same cross-validation partition to avoid dependence-related data leakage.

For each of the 50 repetitions and at each level of analysis, a receiver operating characteristic (ROC) curve and the area under the curve (AUC) were determined, with OA treated as the positive class. The distribution of the resulting AUC values was characterised using the mean, standard deviation, median, and the 25th and 75th percentiles.

For the Mahalanobis distance-based detector, an additional threshold analysis was performed. Decision thresholds were determined exclusively from the anomaly scores obtained for the HC validation set:

$$T_q = P_q(S_M^{HC, val}), q \in \{90, 95\}, \quad (5)$$

where $P_q(\cdot)$ denotes the q -th percentile of the distribution, and $S_M^{HC, val}$ denotes the Mahalanobis distance values obtained for the HC validation set. An observation was considered an outlier if $S_M > T_q$. Thresholds were determined independently for the Cycle, Unit, and Patient levels, after applying the appropriate aggregation of the validation data.

For both thresholds, sensitivity, specificity, false positive rate (FPR), and balanced accuracy were calculated. For each metric, the mean and standard deviation across the 50 repetitions were reported. Throughout the entire procedure, OA data were used exclusively at the final evaluation stage and had no influence on feature normalisation, estimation of the reference model parameters, or determination of the decision thresholds.

3. RESULTS

The results are presented sequentially for the characteristics of VAG signals and the performance of the four anomaly detection methods, evaluated at the cycle, joint, and patient levels. Subsequently, for the best detector, a threshold analysis was conducted using the P90 and P95 thresholds derived from the healthy reference distribution, corresponding to 10% and 5% upper-tail exceedance rates, respectively, to assess sensitivity, specificity, balanced accuracy, and false positive rate.

Normalised VAG signal cycles for the HC and OA groups are shown in Figure 2. In both groups, the waveforms were characterised by a complex temporal structure comprising segments with relatively stable amplitudes and abrupt local changes in signal values. Distinct differences in shape were also evident among the three representative waveforms labelled Q25, median, and Q75, in both the HC and OA groups. The presented waveforms did not indicate a simple, one-dimensional separation of the groups based solely on signal shape or amplitude; therefore, further comparison was based on multidimensional anomaly detection results.

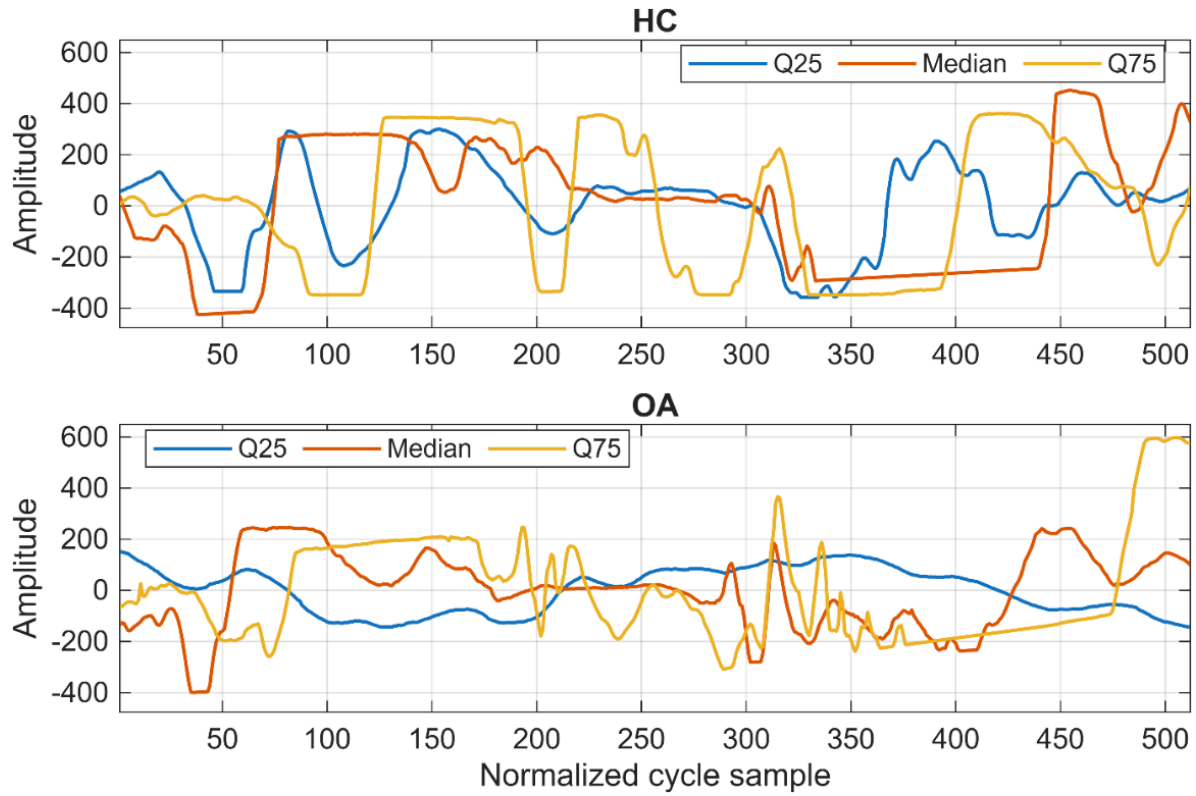


Fig. 2. Normalised vibroarthrographic (VAG) signal cycles in the healthy control (HC) group and in patients with knee osteoarthritis (OA)

A comparison of four anomaly detection methods showed that the Mahalanobis distance achieved the highest ROC AUC at each analysed aggregation level (Table 1, Figure 3). At the cycle level, the AUC for this method was 0.703 ± 0.049 ; at the joint level, 0.731 ± 0.059 ; and at the participant level, 0.729 ± 0.075 . For One-Class SVM, these values were 0.695 ± 0.042 , 0.711 ± 0.047 , and 0.694 ± 0.051 , respectively, while for the Euclidean-distance-based models, they were 0.683 ± 0.045 , 0.693 ± 0.047 , and 0.683 ± 0.053 . The lowest AUC values in each variant were obtained for Isolation Forest: 0.665 ± 0.046 at the cycle level, 0.678 ± 0.053 at the unit level, and 0.662 ± 0.060 at the participant level.

The highest AUC across all combinations of method and aggregation level was 0.731 ± 0.059 , obtained with the Mahalanobis distance at the joint level. The patient-level result for the same method was very similar, at 0.729 ± 0.075 . At the participant level, the AUC difference between the Mahalanobis distance and the next method in the ranking, One-Class SVM, was 0.035, while the differences relative to the robust Euclidean distance and Isolation Forest were 0.046 and 0.067, respectively.

At the unit level, higher AUC values were obtained than at the cycle level for all four detectors. The increase was 0.028 for the Mahalanobis distance, 0.016 for One-Class SVM, 0.010 for the robust Euclidean distance, and 0.013 for Isolation Forest. In contrast, aggregation to the patient level was associated with a higher AUC than at the cycle level, primarily for the Mahalanobis distance (0.729 vs 0.703); for the other methods, the patient-level values were similar to or slightly lower than the cycle-level values.

Tab. 1. Comparison of the effectiveness of four anomaly detection methods based on the area under the ROC curve (ROC AUC) at the cycle, unit, and patient levels

Method	Cycle-level AUC	Joint-level AUC	Participant-level AUC
Mahalanobis	0.703 ± 0.049	0.731 ± 0.059	0.729 ± 0.075
One-Class SVM	0.695 ± 0.042	0.711 ± 0.047	0.694 ± 0.051
Robust Euclidean	0.683 ± 0.045	0.693 ± 0.047	0.683 ± 0.053
Isolation Forest	0.665 ± 0.046	0.678 ± 0.053	0.662 ± 0.060

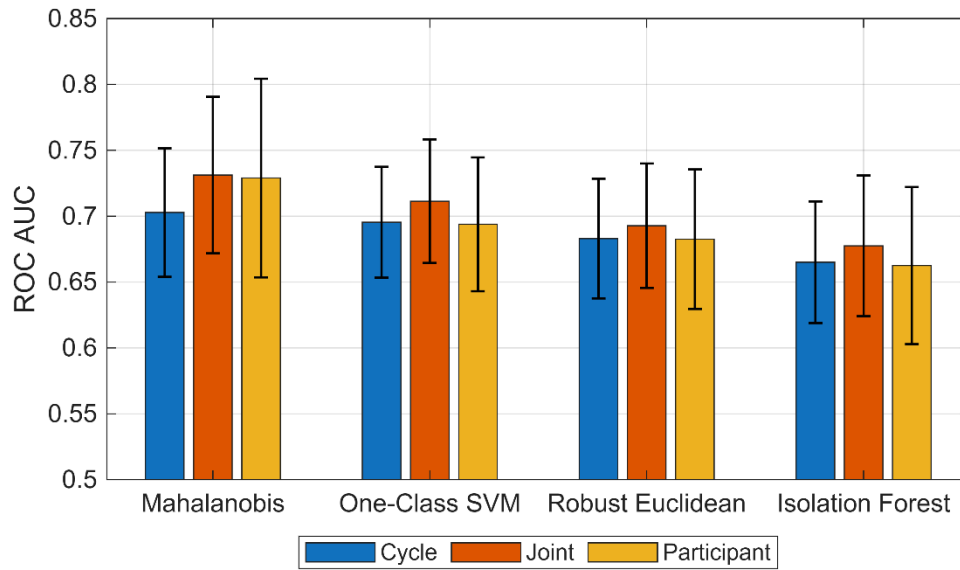


Fig. 3. Comparison of ROC AUC values for Mahalanobis distance, One-Class SVM, robust Euclidean distance, and Isolation Forest at the cycle, joint, and participant levels

The distribution of participant-level ROC AUC values is shown in Figure 4. The distributions for the individual methods partially overlapped; however, the Mahalanobis distance values were shifted toward higher AUCs than those of the other detectors, consistent with the summary results presented in Table 1. At the same time, the Mahalanobis distance method exhibited the highest reported variability in participant-level values (0.729 ± 0.075), while the standard deviation was 0.051 for One-Class SVM, 0.053 for robust Euclidean distance, and 0.060 for Isolation Forest. The graph also showed isolated lower outliers for One-Class SVM and robust Euclidean distance.

Despite the variability among the values comprising the presented distributions, the ranking of the methods at the participant level remained consistent with the AUC values: Mahalanobis distance achieved the highest score (0.729 ± 0.075), followed by One-Class SVM (0.694 ± 0.051), robust Euclidean distance (0.683 ± 0.053), and Isolation Forest (0.662 ± 0.060).

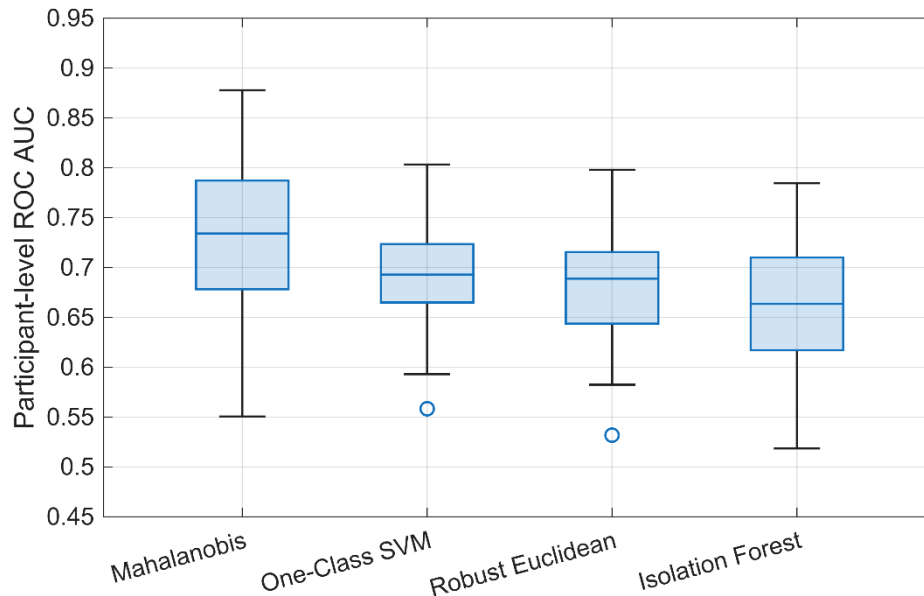


Fig. 4. Distribution of participant-level ROC AUC values for the four anomaly detection methods analysed: Mahalanobis distance, One-Class SVM, robust Euclidean distance, and Isolation Forest

For the model with the highest AUC values, an additional evaluation was conducted using the P90 and P95 thresholds (Table 2). At the P90 threshold, sensitivity was 0.273 ± 0.116 at the cycle level, 0.338 ± 0.161 at the joint level, and 0.386 ± 0.202 at the participant level. The corresponding specificity values were $0.881 \pm$

0.082, 0.881 ± 0.117 , and 0.868 ± 0.164 , and the balanced accuracy values were 0.577 ± 0.036 , 0.610 ± 0.051 , and 0.627 ± 0.062 , respectively. The false positive rates (FPRs) were 0.119, 0.119, and 0.133, respectively.

With a more restrictive P95 threshold, sensitivity decreased to 0.163 ± 0.087 at the cycle level, 0.223 ± 0.127 at the joint level, and 0.351 ± 0.201 at the participant level. At the same time, specificity was 0.935 ± 0.063 , 0.933 ± 0.086 , and 0.883 ± 0.159 , respectively, while balanced accuracy was 0.549 ± 0.024 , 0.578 ± 0.044 , and 0.617 ± 0.061 . The FPR was 0.065, 0.067, and 0.118, respectively.

Increasing the threshold from P90 to P95 was associated with a decrease in FPR at all levels of aggregation: from 0.119 to 0.065 at the cycle level, from 0.119 to 0.067 at the joint level, and from 0.133 to 0.118 at the participant level. This was accompanied by a decrease in sensitivity and balanced accuracy. Balanced accuracy was higher for P90 than for P95 at each of the three levels: 0.577 vs 0.549 at the cycle level, 0.610 vs 0.578 at the joint level, and 0.627 vs 0.617 at the participant level.

The highest balanced accuracy among all threshold assessments was obtained at the participant level with P90 (0.627 ± 0.062); this configuration also yielded the highest sensitivity (0.386 ± 0.202) and a specificity of 0.868 ± 0.164 . The highest specificity and lowest FPR, however, were obtained at the cycle level at P95 (0.935 ± 0.063 and 0.065, respectively) with a sensitivity of 0.163 ± 0.087 . In none of the six threshold variants analysed did sensitivity exceed 0.386; specificity ranged from 0.868 to 0.935, and balanced accuracy from 0.549 to 0.627.

Figure 5 presents the participant-level threshold results in detail. For P90, sensitivity, specificity, and balanced accuracy were 0.386 ± 0.202 , 0.868 ± 0.164 , and 0.627 ± 0.062 , respectively, while for P95 they were 0.351 ± 0.201 , 0.883 ± 0.159 , and 0.617 ± 0.061 , respectively.

Tab. 2. Sensitivity, specificity, balanced accuracy, and false positive rate (FPR) for the best anomaly detection model at the P90 and P95 thresholds, evaluated at the cycle, joint, and participant levels

Level	Threshold	Sensitivity	Specificity	Balanced accuracy	FPR
Cycle	P90	0.273 ± 0.116	0.881 ± 0.082	0.577 ± 0.036	0.119
Cycle	P95	0.163 ± 0.087	0.935 ± 0.063	0.549 ± 0.024	0.065
Joint	P90	0.338 ± 0.161	0.881 ± 0.117	0.610 ± 0.051	0.119
Joint	P95	0.223 ± 0.127	0.933 ± 0.086	0.578 ± 0.044	0.067
Participant	P90	0.386 ± 0.202	0.868 ± 0.164	0.627 ± 0.062	0.133
Participant	P95	0.351 ± 0.201	0.883 ± 0.159	0.617 ± 0.061	0.118

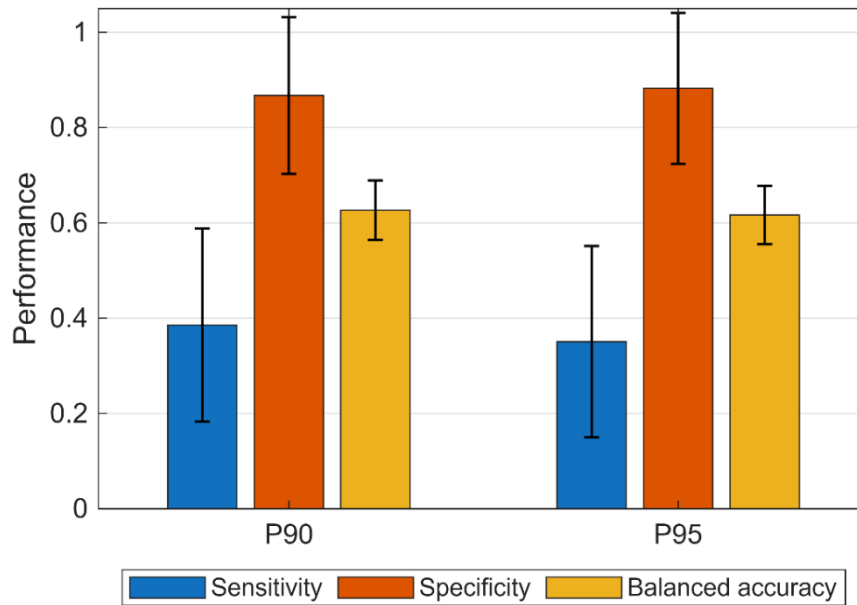


Fig. 5. Sensitivity, specificity, and balanced accuracy of the best participant-level anomaly detection model using the P90 and P95 thresholds

Overall, the results of the method comparison indicated that the Mahalanobis distance had the highest ROC AUC across all three levels of aggregation. In contrast, the evaluation using fixed thresholds showed that specificity outperformed sensitivity in all analysed configurations, with the highest balanced accuracy of 0.627 ± 0.062 for the patient-level evaluation at P90.

4. DISCUSSION

The results indicate that changes associated with knee osteoarthritis can be identified as deviations from the multidimensional VAG feature pattern characteristic of healthy individuals, even though data from patients with OA were not used in model training, standardisation, or the determination of decision thresholds. The Mahalanobis distance achieved the highest performance, with an ROC AUC of 0.703 ± 0.049 at the cycle level, 0.731 ± 0.059 at the joint level, and 0.729 ± 0.075 at the participant level. One-Class SVM, robust Euclidean distance, and Isolation Forest achieved lower AUC values, with Isolation Forest yielding the worst results. At the same time, thresholding the Mahalanobis score at the P90 and P95 levels led to high specificity but limited sensitivity; even in the best-case scenario, sensitivity did not exceed 0.386, and the maximum balanced accuracy was 0.627 ± 0.062 .

These results should be interpreted primarily as confirmation of the feasibility of a different paradigm for VAG analysis, rather than as an attempt to directly outperform classical HC-OA classifiers. In supervised studies, higher diagnostic values were achieved; however, these models used information from both classes during training. For example, time-frequency analysis of knee sounds during walking yielded a ROC AUC of approximately 0.92 (Yiallourides & Naylor, 2021), and a study using wearable acoustic sensors demonstrated the ability to detect even the pre-radiographic form of OA (Nichols et al., 2023). Multichannel vibroarthrography also revealed distinct VAG maps in individuals with painful OA and asymptomatic individuals, as well as a relationship between parameters and the activity being performed (Madeleine et al., 2020). A recent study involving 121 participants also demonstrated significant differences in acoustic emission parameters between healthy knees and those with OA, including differences in amplitude, duration, and signal energy (Verma et al., 2026).

These results are consistent with previous observations regarding the diagnostic potential of VAG frequency characteristics (Befrui et al., 2018) and the relationship between acoustic emissions and kinematic instability and radiographic changes in OA (Nevalainen et al., 2021). The key difference, however, is that in the present study, the threshold for “normality” was established without access to pathology data. For this reason, the moderate AUC of approximately 0.73 can be considered a significant proof-of-concept result: some of the information related to OA is contained in the deviation from the physiological VAG distribution itself, rather than solely in features optimised for a predefined disease class.

The advantage of the Mahalanobis distance over the robust Euclidean distance is particularly interesting because it suggests that diagnostic information may stem not only from the values of individual parameters but also from their mutual configuration. Unlike the Euclidean distance, the Mahalanobis distance accounts for the covariance of features and can therefore identify an observation as an outlier even when no single parameter takes on an extreme value. A similar method for constructing a multidimensional measure of deviation from the norm was applied to personalised white matter imaging anomaly detection, in which the Mahalanobis distance enabled a specific individual’s multidimensional profile to be compared with that of a reference population (Guerrero-Gonzalez et al., 2022).

This result also has methodological significance. Comparative studies on anomaly detection show that greater model complexity does not guarantee better performance, and the way anomalies are represented and identified can be just as important as the algorithm’s architecture itself (Garg et al., 2022). Similar conclusions apply to biomedical biosignals, where lightweight, feature-based anomaly detection algorithms can be effective when computational resources are limited (Baciu et al., 2023). On the other hand, the development of unsupervised and one-class methods suggests that, with sufficiently large reference datasets, it is possible to learn a much richer representation of normality, both using generative models (Pinaya et al., 2022) and hierarchical one-class networks (W. Zhang et al., 2023).

The current Mahalanobis advantage does not, therefore, mean that a simple model will always be optimal, but rather suggests that, with 48 healthy individuals and only eight interpretable features, estimating a relatively simple covariance structure may be more stable than training a more flexible boundary using OC-SVM or partitioning the feature space using Isolation Forest. This is also consistent with the principles of modern one-class methods, which describe a compact region of the reference distribution, and multilayer representations of the normal class (Maziarka et al., 2021; Massoli et al., 2022).

Higher AUC values at the joint level than at the cycle level across all four detectors suggest that aggregating repeated movements reduces the influence of short-term variability not directly related to the joint’s long-term mechanical characteristics. This interpretation is well supported by studies on VAG repeatability. Kalo et al. (2020c) demonstrated high signal repeatability within a single session but markedly lower repeatability across

days, whereas Khokhlova et al. found that the repeatability of acoustic emissions significantly depends on controlling the manner of movement execution, sensor mounting, and minimising motion artefacts (Khokhlova et al., 2022).

The median value across several cycles can therefore serve as a simple filter resistant to individual non-standard movements. At the same time, the lack of further significant improvement after moving from the joint level to the participant level suggests that the mechanical phenotype may primarily be a property of the specific knee rather than of the study participant.

Another important factor is the strong dependence of VAG on biomechanical conditions. The acoustic characteristics of the joint vary with the type of activity (Kalo et al., 2020a), and increased knee load increases the amplitude of the recorded vibrations (Kalo et al., 2020b). This relationship was recently confirmed during squats with a gradually increasing load, in which VAG parameters increased almost linearly with the external load (Borzucka et al., 2026). Furthermore, the acoustic profile may change after a warm-up and exercise, leading to muscle fatigue (Tenberg et al., 2021).

The standardisation of the sit-to-stand movement in the present study is therefore a strength, but it does not eliminate variability in movement speed, individual load distribution, compensatory strategies, or muscle function.

Demographic characteristics may also influence the reference distribution. Studies of healthy individuals have demonstrated age-related changes in acoustic emission parameters (Khokhlova, Komaris, O'Flynn, et al., 2023) and nonlinear VAG parameters (Karpinski et al., 2026; Kręcis et al., 2022).

This is particularly important in the one-class model: if the healthy reference group does not reflect the full range of physiological variability in age, sex, BMI, physical activity, and movement mechanics, part of the anomaly score may reflect individual differences rather than pathology. In the future, it may therefore be more appropriate to develop stratified norms or models that account for these variables, rather than using a single universal normal distribution.

Notably, the HC and OA groups differed in age and BMI, as well as in sex distribution; therefore, part of the observed differences in anomaly scores may potentially reflect demographic and anthropometric factors and their influence on movement mechanics rather than OA-related changes alone. However, the impact of these differences was intended to be minimised through a detailed eligibility and physical examination protocol, including assessments of gait and posture, limb symmetry, range of motion, axial alignment, muscle atrophy, and meniscal and ligamentous stability, thereby supporting more biomechanically and functionally consistent group selection. Nevertheless, residual effects of age, BMI, and other demographic characteristics cannot be completely excluded; therefore, the present findings should be interpreted as deviations from the investigated healthy reference distribution rather than as an OA-specific effect fully independent of potential demographic confounding.

The most significant limitation of the current configuration from a clinical application perspective remains its low sensitivity when thresholds are determined solely by HC. At the P90 level, the model identified approximately 39% of OA cases as anomalous, with a specificity of approximately 87%; at the P95 level, slightly higher specificity was achieved at the cost of a further decrease in sensitivity.

This profile does not currently justify using the method as a standalone screening test to rule out OA. A more appropriate interpretation of the result is that it indicates atypical joint mechanics, which may identify individuals requiring further diagnostic evaluation. It is worth noting that high specificity is not synonymous with high positive predictive value, which also depends on the disease prevalence in the study population.

At the same time, the limited sensitivity does not undermine the biological validity of VAG as a functional biomarker. In an experimental model of progressive cartilage damage, systematic changes in acoustic emission parameters, including signal amplitude and energy, were observed (Khokhlova, Komaris, Davarinos, et al., 2023).

Importantly, acoustic characteristics do not exclusively reflect irreversible structural changes. In patients with OA, acoustic emission parameters changed immediately after a single session of therapeutic exercise (Kalo et al., 2022), and VAG parameters also responded to viscosupplementation (Bączkiewicz et al., 2021).

This implies that the signal may reflect a dynamic combination of articular surface friction, load, neuromuscular control, and synovial fluid properties, rather than merely the radiographic severity of OA. This characteristic is potentially valuable for functional monitoring but simultaneously limits the etiological specificity of anomaly detection.

From a translational perspective, it would therefore be desirable to combine the VAG result with other signals recorded during the same movement task. Wearable systems have already been developed to simultaneously record joint acoustics, bioimpedance, inertial data, and temperature (Teague et al., 2020).

In the study analysed, the angular position of the joint was recorded synchronously, but the eight features primarily represented global characteristics of the entire cycle. The use of information about the phase of movement is particularly promising, as studies have shown that the VAG representation, depending on the joint angle, can improve the integration of functional and structural information (Łysiak et al., 2026). Combining time-frequency features with angular position could therefore prevent the loss of short, local acoustic events that would otherwise result from the median aggregation of entire cycles.

Taken together, these observations support the interpretation of VAG-derived measures as digital functional biomechanical biomarkers that characterise joint behaviour during movement rather than directly reflecting structural disease severity. Their value lies in quantifying deviations in the mechanical-acoustic phenotype from a physiological reference, while their interpretation requires consideration of biomechanical conditions and inter-individual variability. In this context, VAG may provide a complementary source of functional information on joint mechanics, extending structural assessment with a quantitative description of dynamic joint behaviour.

5. LIMITATIONS AND DIRECTIONS FOR FURTHER RESEARCH

A major limitation is, first and foremost, the nature of the OA population studied. Patients were selected for surgical treatment; therefore, the results primarily pertain to clinically significant, advanced disease and cannot be automatically extrapolated to early or pre-radiographic OA. This is particularly important in light of data indicating significant heterogeneity in disease progression: in a large cohort of patients with early OA, multiple distinct trajectories of symptoms and structural changes were identified, with only partial concordance between clinical and radiographic components (Altamirano et al., 2023).

Some patients may therefore exhibit an acoustic-mechanical profile within the healthy population range despite advanced morphological changes, which may explain the low sensitivity observed with restrictive thresholds.

A second limitation is the size of the reference group. Although 50 repetitions of the split increase the reliability of the stability assessment, the normality model was estimated each time based on only about 70% of the 48 healthy participants. The relatively large standard deviation of the Mahalanobis AUC at the patient level (0.075) and the high variability in sensitivity indicate that the composition of the healthy group significantly influences the determined normality threshold.

Another limitation is that the one-class detector identifies a deviation from health rather than OA as a specific aetiology. Meniscal tears, joint instability, patellofemoral pathology, post-traumatic conditions, or other mechanical disorders may also cause an anomalous VAG. Therefore, future validation should include not only HC and OA but also clinically relevant differential groups. It is also worthwhile to compare manually designed features with time-frequency, nonlinear, and automatically learned representations. Current results on multiscale VAG analysis (Machrowska et al., 2025b) and modern single-class models (W. Zhang et al., 2023) suggest potential for increased sensitivity; however, more complex models should be implemented only after a significantly larger, externally validated database of healthy signals has been compiled.

6. CONCLUSIONS

The presented results suggest that OA can manifest as a multidimensional deviation of VAG from an empirically defined physiological norm. Of particular importance is the Mahalanobis distance and the improvement in results following aggregation at the joint level, which highlight the value of accounting for the interdependence between simple, interpretable features and recurring movement cycles. However, the current sensitivity is too low for standalone screening applications. Accordingly, despite the highest mean ROC AUC obtained with the Mahalanobis distance, the overall diagnostic performance should be considered moderate (participant-level AUC: 0.729 ± 0.075 ; maximum balanced accuracy: 0.627 ± 0.062 ; sensitivity ≤ 0.386). These findings should therefore be interpreted as promising proof-of-concept evidence, and larger, more representative cohorts with prospective external validation are required before broader clinical conclusions or screening applications can be considered. The most justified direction for further development

is therefore to treat VAG as a complementary functional biomarker: one based on a large, representative healthy norm, controlling for age and biomechanical conditions, analysing the signal relative to the phase of movement, and validated prospectively and externally. From this perspective, the advantage of the one-class paradigm is not that it competes with imaging or supervised OA diagnosis, but rather that it enables the detection of previously unknown mechanical-acoustic abnormalities in the joint without the need to define the entire spectrum of potential pathologies in the training set.

ABBREVIATIONS

AI – artificial intelligence
AUC – area under the receiver operating characteristic curve
BMI – body mass index
CEEMDAN – complete ensemble empirical mode decomposition with adaptive noise
CKC – closed kinetic chain
DC – direct current
DominantFreqIndex – dominant frequency index
FFT – fast Fourier transform
FPR – false positive rate
HC – healthy control(s)
IMU – inertial measurement unit
MAD – median absolute deviation
MeanAbs – mean absolute amplitude
MRI – magnetic resonance imaging
OA – osteoarthritis
OC-SVM – one-class support vector machine
P90 – 90th percentile
P95 – 95th percentile
Q25 – 25th percentile (first quartile)
Q75 – 75th percentile (third quartile)
RBF – radial basis function
RMS – root mean square
ROC – receiver operating characteristic
SD – standard deviation
Sens – sensitivity
SOM – self-organizing map
Spec – specificity
SVM – support vector machine
TNR – true negative rate
TPR – true positive rate
USB – Universal Serial Bus
VAG – vibroarthrography
val – validation
ZeroCrossRate – zero-crossing rate

Conflicts of Interest

The authors declare no conflict of interest.

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