From Motion Data to Meaning: Towards Human-Centered and Interpretable Movement Analysis Interfaces

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Abstract

While markerless motion capture provides rich biomechanical data for clinical assessments, its integration into everyday orthopedic practice is limited by the abstract nature of kinematic signals and the opacity of standard machine learning models. To bridge this interpretability gap, we present a framework that embeds explainable AI directly into a real-time movement classification engine. Our primary aim is to achieve a dual-interface architecture that transforms model outputs into role-specific visual narratives: (i) a *Clinician Interface* provides analytical dashboards, while a (ii) *Patient Interface* translates technical metrics into engaging and accessible visualizations. This framework highlights the need for a human-centered paradigm to leverage complex biomechanical data and their explanations in clinical decision-making and trust.

CCS Concepts

• **Applied computing → Health informatics**; **Consumer health**; Multi-criterion optimization and decision-making; • **General and reference** → Design; • **Human-centered computing → Graphical user interfaces**; *Collaborative interaction*; **Visualization design and evaluation methods**; **Information visualization**.

Keywords

XAI, Supervised Learning, Diagnostics

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1 Introduction and Motivation

Movement analysis plays a central role in clinical biomechanics, rehabilitation, and motor control research [8, 12]. Traditionally, such analyses rely on marker-based motion-capture systems, which offer high precision but require expensive, lab-based equipment and trained operators. While advances in motion capture technologies such as markerless systems have enabled the acquisition of increasingly detailed biomechanical data, supporting quantitative analysis of human movement in clinical and rehabilitation contexts.

Despite the technological progress, biomechanical data remain largely underutilized in everyday clinical practice [7, 11, 13]. One major barrier lies in interpretability: biomechanical signals are high-dimensional and abstract. While machine learning (ML) techniques can effectively identify patterns, their outputs often lack transparency. To bridge this gap, we developed (1) a robust processing pipeline for markerless motion data, (2) a dual-user interface framework that transforms classification outputs from biomechanical data into role-specific narratives for clinicians and patients, and (3) a computational framework for Human-in-the-Loop validation.

Unlike previous approaches that treat interpretability as a post-hoc layer, we integrate explainable AI (XAI) logic directly into the real-time classification engine. While the data extraction pipeline and baseline clustering were presented in [3], this work describes the development of the real-time classification engine and the interpretable profiling logic. Our goal is to bridge the gap between advanced biomechanical data processing and clinically actionable insights, investigating how supervised movement profiling, combined with explainable ML techniques, can support transparent reasoning about movement patterns while preserving human agency. Rather than treating interpretability as a post-hoc explanation layer, we adopt it as a guiding design principle throughout data processing, model development, and visualization.

2 Background

The integration of digital technologies into healthcare has reshaped how clinical knowledge is produced, interpreted, and communicated. In this context, Machine Learning (ML) has played a central role in supporting diagnostics, prognostics, treatment planning, and patient monitoring [2, 4, 5]. However, the growing presence of ML in clinical workflows has also raised new challenges related to transparency, interpretability, and human oversight.

In parallel, ML has significantly influenced human movement analysis, a domain relevant to rehabilitation, orthopedics, and sports medicine. Biomechanical data pose specific challenges for both modeling and interaction design: movement trajectories are inherently noisy, temporally misaligned, and variable across individuals and repetitions. By processing data from wearable sensors and video recordings, ML-based systems can characterize gait patterns, detect movement impairments, and monitor treatment outcomes [1, 9, 10]. From an HCI perspective, however, the challenge extends beyond identifying meaningful movement phenotypes: clinicians must be

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able to explore and analyze these patterns in ways that align with their expertise and decision-making practices.

Existing tools for motion analysis and ML experimentation are mainly designed for technical users and require programming skills or familiarity with data science workflows, limiting their accessibility in clinical contexts. To overcome this barrier, we propose a web-based interactive system that embeds ML outputs into interfaces supporting data exploration while aligning with clinical intuition. Prior work has shown that interactive dashboards can facilitate understanding of complex biomedical data when combined with intuitive visualizations [6].

3 System Design and Implementation

To investigate these questions, we developed a framework integrating markerless motion capture analysis with explainable ML. The system is designed to be part of a clinical assessment in orthopedics and sports medicine, supporting the evaluation and classification of patients with varying musculoskeletal conditions. Specifically, it processes data from four clinical assessment tasks (Bilateral Squat, Forward Lunge, Lateral Step-Down, and Gait) across three cohorts: subjects with femoroacetabular impingement (FAI), patellofemoral pain (PFP), and healthy controls (HNC).

Classification Architecture. Movement profiling combines two complementary clustering approaches, enabling both biomechanical pattern recognition and clinical risk stratification:

- **Time-series clustering**, utilizing Dynamic Time Warping (DTW) on normalized kinematic curves (101-frame trajectories) to identify movement execution strategies.
- **Discrete clustering**, based on demographics (e.g., age, height, and weight, pathology group) and performance features (e.g., range of motion, strength data of relevant joints).

Explainability for Distance-Based Clustering. Traditional gradient-based XAI methods (SHAP, Grad-CAM) assume differentiable models, incompatible with DTW-based clustering. We address this technical limitation through two adapted techniques, which provide interpretable outputs compatible with the interface layer while respecting the nature of the underlying models:

- **Perturbation-based Feature Attribution:** We implemented a Pseudo-SHAP approach that measures normalized deviations from cluster baselines and attributes specific risk factors (e.g., ROM deficits) to the classification outcome without requiring game-theoretic estimation.
- **Prototype-based Attention Maps:** To replicate the visual utility of Grad-CAM for time-series data, we developed an attention mechanism that computes frame-wise and feature-wise Euclidean distances from the cluster prototype, and highlights the specific temporal phases and joints driving the cluster assignment.

Dual Interface Architecture Design. A core contribution is the *algorithmic transformation* of model outputs into role-specific representations. The implemented system comprises two data exploration modules (Figure 1). The **Clinician Interface Module** generates analytical views supporting investigative workflows and containing risk decomposition (e.g., demographic, strength, movement components), statistical deviation metrics, and flagged features, kinematic attention heatmaps overlaying temporal anomalies,

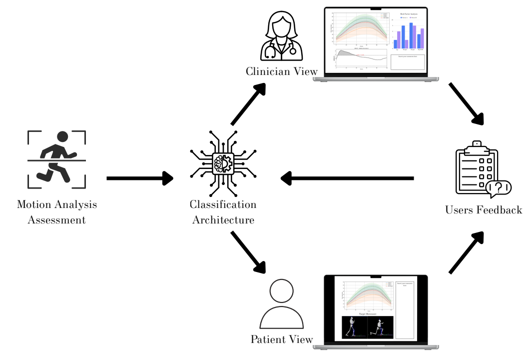

Figure 1: System architecture of the proposed framework, from initial assessment to user-specific interfaces integrated with a feedback loop to continuously refine the model.

cluster context (e.g., similar cases, centroid distances), and explicit uncertainty encoding (e.g., confidence scores, prediction variance). Conversely, the **Patient Interface Module** transforms technical outputs into engagement-oriented feedback, providing simplified movement profile labels, target zone visualizations (current vs. optimal joint ranges), and progress scoring (0–100 scale) with actionable improvement suggestions.

4 Discussion and Future Work

This paper has presented the architectural design and backend implementation of a framework for interpretable movement analysis in clinical contexts. Our primary contribution is demonstrating how distance-based clustering models, common in biomechanical analysis but resistant to standard XAI techniques, can be made interpretable through perturbation-based attribution and prototype-distance attention mechanisms. The dual-interface architecture is a first step towards proving that a single classification pipeline can support divergent user needs through algorithmic transformation rather than separate models.

From an HCI perspective, this work raises two questions about interface-mediated trust: How does explicit uncertainty encoding influence clinician reliance on automated suggestions? Can role-specific transformations of the same data reduce the "interpretation gap" between expert and lay users without oversimplification?

To answer these questions, future work will involve frontend deployment and user study execution. We will recruit clinicians and patients to evaluate the system using a human-in-the-loop framework, specifically investigating agreement between clinician assessment and model classification, and system usability. Furthermore, we plan to (1) extend the patient interface with longitudinal tracking to visualize recovery trajectories across sessions; and (2) investigate counterfactual explanations to enhance actionability. Overall, this work takes a step toward human-centered clinical systems for movement-based patient categorization that promote transparency, agency, and trust for all the involved stakeholders.

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References

[1] Saurabh Arora and Inderveer Chana. 2014. A survey of clustering techniques for big data analysis. In *2014 5th International Conference-Confluence The Next Generation Information Technology Summit (Confluence)*. IEEE, 59–65.

[2] Wadhah Ayadi, Wajdi Elhamzi, Imen Charfi, and Mohamed Atri. 2021. Deep CNN for Brain Tumor Classification. *Neural Processing Letters* 53, 1 (Feb. 2021), 671–700. doi:10.1007/s11063-020-10398-2

[3] Eleonora Cabai. 2025. *Movement-based clustering with integrated web visualization: bridging motion capture and clinical interpretation*. Master's thesis. Politecnico di Milano. https://hdl.handle.net/10589/239538 Master's thesis.

[4] Andreea Ionela Dumachi and Cătălin Buiu. 2024. Applications of Machine Learning in Cancer Imaging: A Review of Diagnostic Methods for Six Major Cancer Types. *Electronics* 13, 2323 (Jan. 2024), 4697. doi:10.3390/electronics13234697

[5] Bradley J. Erickson, Panagiotis Korfiatis, Zeynettin Akkus, and Timothy L. Kline. 2017. Machine Learning for Medical Imaging. *RadioGraphics* 37, 2 (2017), 505–515. arXiv:https://doi.org/10.1148/rg.2017160130 doi:10.1148/rg.2017160130 PMID: 28212054.

[6] Marie-Pierre Gagnon, Steven Ouellet, Eugène Attisso, Wilfried Supper, Samira Amil, Caroline Rhéaume, Jean-Sébastien Paquette, Christian Chabot, Marie-Claude Laferrière, and Maxime Sasseville. 2024. Wearable Devices for Supporting Chronic Disease Self-Management: Scoping Review. *Interact J Med Res* 13 (Dec. 2024), e55925. doi:10.2196/55925

[7] Robert M. Kanko, Elise K. Laende, Elysia M. Davis, W. Scott Selbie, and Kevin J. Deluzio. 2021. Concurrent assessment of gait kinematics using marker-based and markerless motion capture. *Journal of Biomechanics* 127 (Oct. 2021), 110665. doi:10.1016/j.jbiomech.2021.110665

[8] Tung-Wu Lu and Chu-Fen Chang. 2012. Biomechanics of human movement and its clinical applications. *The Kaohsiung Journal of Medical Sciences* 28, 2, Supplement (2012), S13–S25. doi:10.1016/j.kjms.2011.08.004

[9] James MacQueen. 1967. Some methods for classification and analysis of multivariate observations. In *Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability, Volume 1: Statistics*, Vol. 5. University of California press, 281–298.

[10] S. Syafiq Mazlan, M.Z. Ayob, and Z.A. Kadir Bakti. 2017. Anterior cruciate ligament (ACL) injury classification system using support vector machine (SVM). In *2017 International Conference on Engineering Technology and Technopreneurship (ICE2T)*. IEEE, 1–5. doi:10.1109/ICE2T.2017.8215960

[11] Lars Mündermann, Stefano Corazza, and Thomas P. Andriacchi. 2006. The evolution of methods for the capture of human movement leading to markerless motion capture for biomechanical applications. *Journal of NeuroEngineering and Rehabilitation* 3, 6 (2006). doi:10.1186/1743-0003-3-6

[12] Katharine Scrivener and Roberta Shepherd. 2022. The importance of kinesiology, biomechanics and motor learning for movement analysis and clinical reasoning in neuromuscular physiotherapy. *Physical Therapy Reviews* 27, 5 (Sept. 2022), 325–328. doi:10.1080/10833196.2022.2141529

[13] Laura Wade, Richard Needham, Polly McGuigan, Raymond Abboud, Katherine Stannage, Stephanos Solomonidis, and Laurence Kenney. 2022. Applications and limitations of current markerless motion capture methods for clinical gait biomechanics. *PeerJ* 10 (2022), e12995. doi:10.7717/peerj.12995