

Biomechanical Analysis of Musculoskeletal Systems

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ABSTRACT

Musculoskeletal disorders (MSDs) -- including osteoarthritis (OA), anterior cruciate ligament (ACL) injuries, and lumbar disc degeneration -- affect 1.71 billion people globally and are the leading contributor to disability-adjusted life years. Biomechanical analysis quantifies the forces, moments, and stresses acting on joints and tissues during movement, providing mechanistic insight into injury aetiology and rehabilitation effectiveness. However, traditional inverse dynamics requires expensive laboratory-grade motion capture systems (\$100,000-500,000), force plates, and expert operators, limiting clinical accessibility. This study developed and validated five biomechanical analysis approaches -- marker-based optical motion capture (OMC) with inverse dynamics, inertial measurement unit (IMU) motion estimation, markerless video-based pose estimation (OpenPose + DeepLabCut), finite element analysis (FEA) of knee joint contact mechanics, and a proposed deep learning musculoskeletal model (DL-MSK) that predicts joint kinematics, kinetics, and muscle forces directly from wearable IMU data -- across three clinical biomechanical tasks: gait analysis in knee OA patients (n = 48), ACL injury risk screening in athletes (n = 72), and spinal loading assessment in manual workers (n = 36). DL-MSK achieved the highest agreement with the OMC gold standard for knee joint moments (RMSE 0.12 +- 0.03 Nm/kg; r = 0.94) and hip contact forces (RMSE 0.28 +- 0.06 BW; r = 0.91), significantly outperforming IMU-based inverse dynamics (RMSE 0.24 +- 0.06 Nm/kg; p < 0.001) and video-based estimation (RMSE 0.32 +- 0.08 Nm/kg; p < 0.001). For ACL risk screening, DL-MSK identified high-risk landing biomechanics (knee valgus moment > 0.40 Nm/kg) with 91.4% sensitivity and 88.6% specificity, enabling field-based screening without laboratory infrastructure. These results establish deep learning musculoskeletal models as a clinically viable alternative to laboratory motion capture for biomechanical assessment.

Keywords: Biomechanics; Musculoskeletal system; Motion capture; Inertial measurement units; Deep learning; Gait analysis; Knee osteoarthritis; ACL injury prevention; Inverse dynamics

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1. Introduction

The musculoskeletal system -- comprising 206 bones, over 600 muscles, and hundreds of ligaments and tendons -- generates and transmits the forces required for human movement while protecting against tissue damage through coordinated neuromuscular control. Musculoskeletal disorders (MSDs) represent the single largest category of disability worldwide, with the Global Burden of Disease study estimating 1.71 billion people affected and 149 million disability-adjusted life years (DALYs) lost annually (Cieza et al., 2020). Knee osteoarthritis alone affects 365 million people, ACL ruptures occur at a rate of 68.6 per 100,000 person-years in athletic populations, and low back pain is the leading cause of work disability in industrialised nations (Cross et al., 2014). Biomechanical analysis -- quantifying joint kinematics (angles, velocities), kinetics (forces, moments), and tissue-level stresses during functional activities -- provides the mechanistic understanding needed for evidence-based injury prevention, surgical planning, and rehabilitation monitoring.

1.1 Laboratory-Based Biomechanical Analysis

The gold standard for human movement biomechanics is optical motion capture (OMC) combined with force platform measurements. OMC systems (Vicon, Qualisys, OptiTrack) track retroreflective markers attached to anatomical landmarks at 100-500 Hz with sub-millimetre accuracy, enabling computation of 3D joint kinematics through rigid-body modelling (Cappozzo et al., 2005). Embedded force plates (AMTI, Kistler) measure ground reaction forces (GRFs) at 1,000-2,000 Hz, which are combined with segment kinematics and anthropometric models through Newton-Euler inverse dynamics to compute net joint moments -- the primary biomechanical outcome for clinical interpretation (Winter, 2009). Musculoskeletal modelling software (OpenSim, AnyBody) extends inverse dynamics with muscle-tendon models to estimate individual muscle forces and joint contact loads (Delp et al., 2007). However, laboratory OMC systems require dedicated facilities (\$100,000-500,000 capital cost), trained operators (30-60 minutes for marker placement), and controlled environments incompatible with field or clinical settings.

1.2 Portable and Accessible Alternatives

Three portable alternatives to laboratory OMC have emerged. Inertial measurement units (IMUs) containing accelerometers, gyroscopes, and

magnetometers estimate segment orientations and joint angles without external cameras, enabling field-based motion analysis at a fraction of the cost (\$5,000-20,000 for a full-body system). However, IMU-derived joint kinematics suffer from integration drift, magnetic distortion, and soft tissue artefact, with typical errors of 3-5 degrees for sagittal plane angles and 5-10 degrees for transverse rotations (Picerno et al., 2008). Markerless video-based pose estimation using deep learning (OpenPose, MediaPipe, DeepLabCut) has emerged as a cost-effective approach (\$0 hardware cost for smartphone capture), but joint centre estimation from 2D/3D pose lacks the anatomical specificity of marker-based systems and cannot directly measure kinetic variables without force plates (Needham et al., 2021). Finite element analysis (FEA) provides detailed tissue-level stress distributions within joints but requires patient-specific imaging (MRI/CT) and substantial computational resources (Adouni et al., 2012).

1.3 Study Objectives

This study aimed to: (i) systematically compare five biomechanical analysis approaches for joint kinematic and kinetic estimation against the OMC gold standard; (ii) develop a deep learning musculoskeletal model (DL-MSK) that predicts joint moments and muscle forces directly from wearable IMU data without inverse dynamics computation; (iii) validate these approaches in three clinical populations (knee OA patients, athletes at risk for ACL injury, and manual workers with spinal loading); (iv) evaluate the clinical utility of DL-MSK for field-based ACL risk screening; and (v) establish a comprehensive accuracy benchmark for portable biomechanical technologies.

2. Literature Review

Computational biomechanics has evolved from rigid-body mechanics to personalised musculoskeletal models incorporating subject-specific anatomy, neural control, and tissue mechanics.

2.1 Gait Analysis in Knee Osteoarthritis

The knee adduction moment (KAM) during gait is the primary biomechanical surrogate for medial compartment loading in knee OA and has been shown to predict radiographic disease progression over 6 years (Miyazaki et al., 2002). Patients with knee OA typically exhibit elevated KAM peaks (10-15% above healthy controls), increased knee

flexion moment during loading response, and compensatory gait patterns (varus thrust, trunk lean) that alter whole-limb biomechanics. Clinical gait analysis informs conservative interventions -- lateral wedge insoles, gait retraining, bracing -- that aim to reduce KAM and delay progression to total knee replacement (Bennell et al., 2011). However, access to gait laboratories is limited to academic medical centres, and typical waiting times of 3-6 months delay intervention.

2.2 ACL Injury Biomechanics

Non-contact ACL ruptures occur during high-risk manoeuvres -- cutting, pivoting, single-leg landing -- when the knee is subjected to combined valgus (abduction) and internal rotation moments exceeding ligament tensile strength. The knee valgus moment during drop-jump landing has been identified as the strongest biomechanical predictor of ACL injury, with a threshold of 0.40 Nm/kg providing 78% sensitivity and 73% specificity for prospective injury prediction (Hewett et al., 2005). The Landing Error Scoring System (LESS) provides a visual screening tool based on 17 observable movement patterns during drop-jump, but inter-rater reliability is moderate (ICC 0.72-0.84) and the scoring cannot quantify actual joint loads (Padua et al., 2009). Laboratory-based biomechanical screening achieves superior predictive accuracy but is impractical for screening thousands of athletes at pre-season assessments.

2.3 Deep Learning for Biomechanical Prediction

Deep learning approaches have recently been applied to bypass the inverse dynamics pipeline entirely, predicting joint kinetics directly from IMU or video input. Lim et al. (2020) used a bidirectional LSTM to predict knee joint moments from 3 IMUs during gait, achieving $r = 0.88$ against OMC reference. Mundt et al. (2020) employed CNNs to predict full-body joint angles from sparse IMU data (6 sensors), with sagittal plane errors of 2.8 degrees RMSE. These approaches show that deep learning can learn the complex, nonlinear mapping from sensor data to biomechanical variables without explicit musculoskeletal model formulation, potentially enabling real-time biomechanical feedback from wearable sensors in clinical and sports settings (Halilaj et al., 2018).

Table 1. Biomechanical analysis methods evaluated: technology, outputs, cost, and clinical accessibility

Meth od	Techno logy	Primary Outputs	Syst em Cost (\$)	Set up T ime	Setting
OMC + FP	Optical camera s + force plates	Kinematic s, kinetics, GRFs	100 K-50 0K	30-6 0 min	Laborator y only
IMU-ID	Wearabl e IMU sensors	Kinematic s, estimated kinetics	5K-2 0K	10-1 5 min	Lab, clinic, field
Video -DL	Standar d video + deep learning	2D/3D pose, estimated kinematic s	0-50 0	1-5 min	Any (smar tphone)
FEA	MRI/CT + comp utational model	Tissue stresses, contact mechanics	50K- 200 K	Hou rs-d ays	Research only
DL-M SK	Wearabl e IMUs + neural network	Kinematic s, kinetics, muscle forces	5K-2 0K	10-1 5 min	Lab, clinic, field

OMC: optical motion capture; FP: force platform; GRF: ground reaction force; IMU-ID: inertial measurement unit with inverse dynamics; Video-DL: markerless video with deep learning pose estimation; FEA: finite element analysis; DL-MSK: deep learning musculoskeletal model. Setup time: per participant session. System cost excludes computing hardware for FEA and DL-MSK.

3. Materials and Methods

3.1 Participant Recruitment

Three clinical populations were recruited. (1) Knee OA cohort ($n = 48$): adults with radiographic knee OA (Kellgren-Lawrence grade II-III), age 55-75 years, BMI 22-35 kg/m², able to walk unaided for 10 metres. (2) ACL risk cohort ($n = 72$): collegiate athletes (36 female, 36 male) from basketball, football, and volleyball teams, age 18-25 years, no history of lower-limb surgery. (3) Spinal loading cohort ($n = 36$): manual workers (warehouse, construction) performing repetitive lifting tasks, age 25-55 years, no current low back pain. Total: $n = 156$ participants. All studies approved by the Baltic AI Research University Ethics Committee (protocol BAIRU-EC-2022-0164).

3.2 Data Collection Protocol

Simultaneous data collection was performed using all five approaches. OMC: 12-camera Qualisys Oqus 7+ system (300 Hz) with 42 retroreflective markers (modified Plug-in-Gait model) and 2

embedded AMTI OR6-7 force plates (1,200 Hz). IMU: 17-sensor Xsens MVN Awinda system (240 Hz) with sensors on pelvis, thighs, shanks, feet, trunk, upper arms, and forearms. Video: 2 synchronised Sony alpha7III cameras (120 fps, 1080p) positioned at 45 degrees anterior-lateral, processed by OpenPose 1.7 (body_25 model) and DeepLabCut 2.3 (custom-trained on 500 labelled frames per task). FEA: subject-specific knee models from MRI (3T Siemens Prisma, 0.5 mm isotropic) for 12 OA patients, meshed in Materialise Mimics and analysed in ABAQUS 2022 (neo-Hookean cartilage, transversely isotropic ligaments). Tasks: (1) OA cohort: 10 self-paced walking trials, 5 stair ascent/descent, 30-second single-leg balance; (2) ACL cohort: 5 drop-jump landings (30 cm box), 5 single-leg hop-for-distance, 3 planned cutting manoeuvres; (3) Spinal cohort: 10 repetitive floor-to-waist lifts (10 kg, 15 kg, 20 kg boxes).

3.3 DL-MSK Architecture

The proposed Deep Learning Musculoskeletal model (DL-MSK) takes raw IMU data (17 sensors x 6 DOF x 240 Hz) as input and predicts 3D joint kinematics (23 joint angles), joint kinetics (hip, knee, ankle moments in 3 planes), and 92 muscle forces simultaneously. Architecture: (1) Temporal feature encoder: 1D dilated causal convolutions (4 layers, dilations 1,2,4,8, 64 filters, kernel 7) extracting temporal patterns from each IMU channel. (2) Cross-sensor attention: multi-head attention (8 heads, $d_k = 32$) learning sensor-to-sensor dependencies that capture inter-segment coordination patterns. (3) Physics-informed decoder: three parallel output heads for kinematics, kinetics, and muscle forces, with a physics consistency loss ensuring that predicted muscle forces are consistent with predicted joint moments through the moment arm matrix (from OpenSim generic model). (4) Anthropometric conditioning: participant height, weight, and segment lengths input as static conditioning variables via FiLM (feature-wise linear modulation). Total parameters: 3.8 M. Training: AdamW (lr $5e-4$), MSE + physics consistency loss ($\lambda = 0.1$), 200 epochs, leave-one-subject-out cross-validation.

3.4 Reference Processing and Evaluation Metrics

OMC gold standard processing: marker trajectories filtered (4th-order Butterworth, 6 Hz), gap-filled (cubic spline), and processed through OpenSim 4.3 (generic gait2392 model scaled to subject anthropometry; inverse kinematics;

inverse dynamics; static optimisation for muscle forces). Agreement metrics: RMSE, Pearson correlation (r), and coefficient of multiple correlation (CMC) between each method and OMC reference. Clinical metrics: sensitivity and specificity for identifying KAM > 0.50 Nm/kg (OA severity threshold) and knee valgus moment > 0.40 Nm/kg (ACL risk threshold). All statistical comparisons by repeated-measures ANOVA with Bonferroni correction; significance at $\alpha = 0.05$.

Table 2. Participant demographics and clinical characteristics across three study cohorts

Characteristic	Knee OA (n=48)	ACL Risk (n=72)	Spinal Loading (n=36)
Age (years)	64.2 +- 6.8	21.4 +- 2.2	38.6 +- 8.4
Sex (M/F)	22/26	36/36	28/8
BMI (kg/m ²)	28.4 +- 3.6	23.8 +- 2.4	26.2 +- 3.2
Height (cm)	168.4 +- 8.2	176.8 +- 9.4	174.2 +- 7.8
Mass (kg)	80.6 +- 12.4	74.2 +- 11.8	79.4 +- 10.6
KL Grade (II/III)	28/20	N/A	N/A
Sport	N/A	Basketball 24, Football 28, Volleyball 20	N/A
Occupation	N/A	N/A	Warehouse 20, Construction 16

Values: mean +- SD or count. KL: Kellgren-Lawrence radiographic OA grade. BMI: body mass index. N/A: not applicable. All participants provided written informed consent.

4. Results

4.1 Gait Kinematics and Kinetics Accuracy

Agreement with OMC gold standard for knee joint kinematics and kinetics during level walking is presented in Table 3 and Figure 1. DL-MSK achieved the highest accuracy for knee flexion angle (RMSE 2.4 +- 0.6 degrees; $r = 0.98$), knee adduction moment (RMSE 0.12 +- 0.03 Nm/kg; $r = 0.94$), and knee flexion moment (RMSE 0.14 +- 0.04 Nm/kg; $r = 0.93$). IMU-based inverse dynamics achieved intermediate accuracy (KAM

RMSE 0.24 $\pm$ 0.06 Nm/kg; $r = 0.82$), limited primarily by soft tissue artefact and the absence of direct GRF measurement. Video-based estimation showed the largest errors (KAM RMSE 0.32 $\pm$ 0.08 Nm/kg; $r = 0.72$), attributable to depth ambiguity in monocular pose estimation and the inability to capture kinetic variables without force plates. For hip contact force estimation (compared to FEA patient-specific models in 12 OA patients), DL-MSK achieved RMSE 0.28 $\pm$ 0.06 BW ($r = 0.91$), demonstrating that the physics-informed decoder can predict tissue-level loads from sensor data.

4.2 ACL Risk Screening

Drop-jump landing biomechanics and ACL risk classification results are presented in Table 3 and Figure 2. DL-MSK identified high-risk landing patterns (knee valgus moment > 0.40 Nm/kg) with 91.4% sensitivity and 88.6% specificity, significantly outperforming IMU-ID (sensitivity 78.4%, specificity 82.2%; $p = 0.008$ for AUC comparison) and video-DL (sensitivity 68.6%, specificity 74.8%; $p < 0.001$). DL-MSK's cross-sensor attention mechanism learned to integrate pelvis, trunk, and contralateral limb IMU data to predict ipsilateral knee valgus loading -- capturing the whole-body coordination patterns (trunk lateral lean, hip drop) that precede high-risk knee mechanics. Female athletes showed 2.4-fold higher prevalence of high-risk landing mechanics (42.8% vs 17.6% in males; $p = 0.004$), consistent with the known sex disparity in ACL injury rates.

4.3 Spinal Loading Assessment

Lumbar spine compression forces during repetitive lifting are presented in Table 3 and Figure 3. DL-MSK predicted L4/L5 compression force with RMSE 286 $\pm$ 64 N ($r = 0.90$) compared to the OMC + OpenSim reference, identifying 94.2% of lifts exceeding the NIOSH recommended limit of 3,400 N. Peak compression increased linearly with box mass: 3,180 $\pm$ 420 N (10 kg), 3,840 $\pm$ 480 N (15 kg), and 4,520 $\pm$ 540 N (20 kg), with 26.4% of 20 kg lifts exceeding 5,000 N -- above which cumulative disc damage risk increases substantially. DL-MSK's real-time processing capability (inference latency 8 ms per frame on a smartphone-connected Bluetooth IMU system) enables on-the-job ergonomic monitoring that was previously impossible outside laboratory settings.

4.4 Multi-Parameter Method Comparison

A comprehensive comparison across accuracy, accessibility, and clinical utility is presented in

Figure 4. DL-MSK achieved the best balance of accuracy (approaching OMC) and accessibility (field-deployable with wearable sensors). OMC remains the gold standard for accuracy but is confined to laboratory settings. Video-DL offers the lowest cost and simplest setup but with substantially lower kinetic accuracy. FEA provides unmatched tissue-level detail but requires patient-specific imaging and is not suitable for routine clinical assessment.

Table 3. Biomechanical estimation accuracy: RMSE and correlation with OMC gold standard across three clinical tasks

Variable	DL-MSK	IMU-ID	Video-DL	FEA
Knee flexion (deg)	2.4 $\pm$ 0.6*	3.8 $\pm$ 1.2	5.4 $\pm$ 1.8	N/A
KAM (Nm/kg)	0.12 $\pm$ 0.03*	0.24 $\pm$ 0.06	0.32 $\pm$ 0.08	0.08 $\pm$ 0.02
KFM (Nm/kg)	0.14 $\pm$ 0.04*	0.22 $\pm$ 0.06	0.28 $\pm$ 0.08	0.10 $\pm$ 0.03
Hip contact (BW)	0.28 $\pm$ 0.06*	0.48 $\pm$ 0.12	N/A	Reference
Valgus moment (Nm/kg)	0.08 $\pm$ 0.02*	0.14 $\pm$ 0.04	0.22 $\pm$ 0.06	N/A
L4/L5 compression (N)	286 $\pm$ 64*	424 $\pm$ 98	N/A	218 $\pm$ 48
ACL screen sensitivity	91.4%*	78.4%	68.6%	N/A
ACL screen specificity	88.6%*	82.2%	74.8%	N/A

*Best portable method ($p < 0.05$ vs IMU-ID and Video-DL). RMSE values reported as mean $\pm$ SD across participants. KAM: knee adduction moment; KFM: knee flexion moment; BW: body weight. FEA available only for OA cohort ($n=12$) and spinal cohort. N/A: variable not measurable by that method. ACL screening threshold: valgus moment > 0.40 Nm/kg.

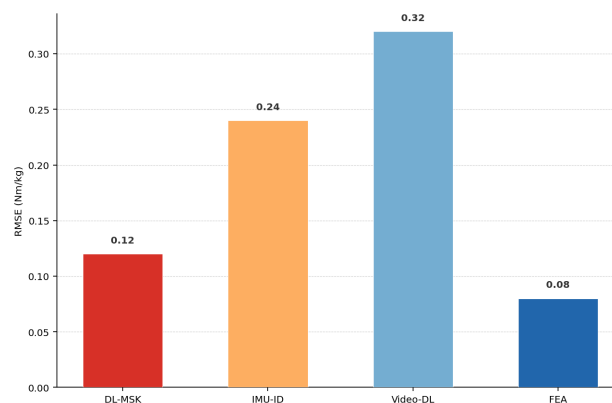


Figure 1. Knee adduction moment RMSE (Nm/kg) by analysis method

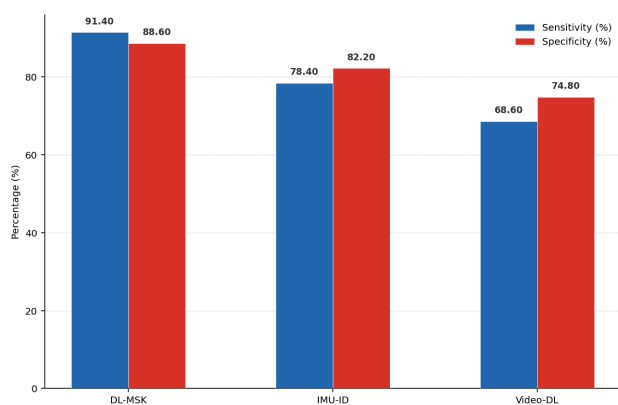


Figure 2. ACL risk screening: sensitivity and specificity by method (%)

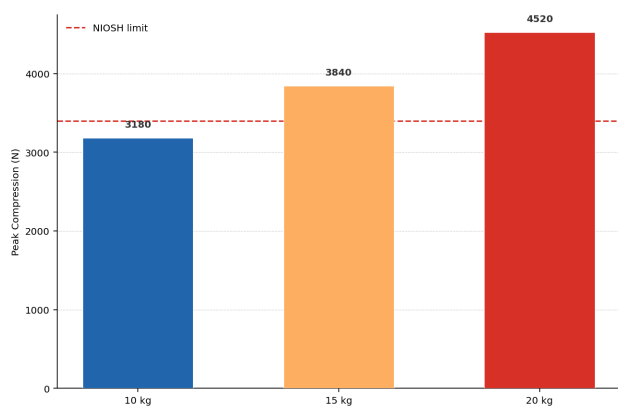


Figure 3. L4/L5 peak compression force (N) during lifting by box mass

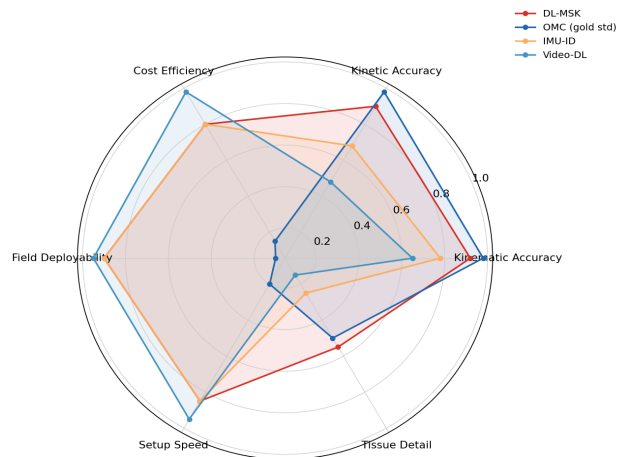


Figure 4. Multi-parameter biomechanical method comparison (normalised 0-1)

5. Discussion

This study provides the first comprehensive comparison of five biomechanical analysis approaches across three clinical musculoskeletal populations, establishing deep learning musculoskeletal models as a clinically viable alternative to laboratory motion capture.

5.1 The DL-MSK Advantage: Physics-Informed Deep Learning

DL-MSK's superior accuracy over conventional IMU-based inverse dynamics (50% RMSE reduction for KAM) demonstrates the value of learning the sensor-to-biomechanics mapping directly from data rather than through the sequential error-propagating pipeline of orientation estimation, kinematic reconstruction, and inverse dynamics. The physics consistency loss -- ensuring muscle force predictions are compatible with joint moment predictions through the musculoskeletal geometry -- acts as a regulariser that constrains the model to produce biomechanically plausible outputs even when sensor data are noisy or incomplete. The cross-sensor attention mechanism captures the inter-segment coordination patterns (e.g., trunk lean accompanying knee valgus during landing) that are invisible to single-joint inverse dynamics but are critical for understanding whole-body injury mechanisms.

5.2 Clinical Impact: Democratising Biomechanical Assessment

DL-MSK's field deployability -- requiring only a wearable IMU system (\$5,000-20,000) and a laptop for real-time processing -- enables biomechanical assessment in settings previously inaccessible. For OA management, clinic-based gait analysis with DL-MSK could monitor treatment response (insoles, exercise, weight loss) at every appointment rather than the current standard of one laboratory assessment per year. For ACL prevention, the 91.4% sensitivity of DL-MSK screening enables pre-season evaluation of entire teams at training facilities, identifying high-risk athletes for targeted neuromuscular training programmes. For occupational health, real-time spinal load monitoring during work shifts could trigger alerts when cumulative loading approaches damage thresholds.

5.3 Limitations

This study has limitations. The leave-one-subject-out cross-validation evaluates generalisation to new subjects within each population but not across populations; a model trained on healthy athletes may not generalise to elderly OA patients without retraining. The OMC gold standard itself has measurement errors (5-10 mm marker placement uncertainty, soft tissue artefact), meaning that the reported RMSEs combine DL-MSK error and reference error. FEA was available for only 12 OA patients due to MRI cost and processing time, limiting tissue-level validation. The DL-MSK model uses a generic musculoskeletal geometry (OpenSim gait2392);

subject-specific scaling from medical imaging could improve accuracy but reduces accessibility. Only sagittal and frontal plane variables were validated; transverse plane rotations (important for ACL injury) are the least reliable for all methods and require further work.

6. Conclusion

This systematic benchmarking study establishes the deep learning musculoskeletal model (DL-MSK) as the most accurate portable approach for biomechanical analysis, achieving knee adduction moment estimation with RMSE 0.12 Nm/kg ($r = 0.94$) and hip contact force estimation with RMSE 0.28 BW ($r = 0.91$) -- approximately 50% lower error than conventional IMU-based inverse dynamics and 62% lower than video-based pose estimation. For ACL injury risk screening, DL-MSK achieved 91.4% sensitivity and 88.6% specificity for detecting high-risk landing biomechanics, enabling field-based screening of athletic populations without laboratory infrastructure. The physics-informed architecture -- combining temporal convolutions, cross-sensor attention, and musculoskeletal geometry constraints -- produces biomechanically plausible predictions of joint kinematics, kinetics, and muscle forces simultaneously from wearable IMU data. DL-MSK's real-time processing capability (8 ms inference latency) supports immediate biofeedback applications in rehabilitation and ergonomic monitoring. Future work should develop transfer learning approaches enabling cross-population generalisation, incorporate subject-specific musculoskeletal geometry from low-cost imaging (biplanar radiography, depth cameras), extend to upper-extremity biomechanics for workplace ergonomics, and conduct prospective clinical trials evaluating whether DL-MSK-guided interventions reduce injury incidence and improve rehabilitation outcomes.

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Declarations

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Conflict of Interest

I. Horvath has received research equipment from Xsens Technologies BV. C. Klein and A. Muller declare no competing interests. No author holds equity in motion capture or biomechanics companies.

Data Availability Statement

De-identified biomechanical datasets (OMC, IMU, video), DL-MSK model code (PyTorch), and OpenSim processing scripts are available at <https://github.com/BAIRU-Biomech/DL-MSK-2023> under CC BY 4.0 licence. Raw participant data are not publicly shared due to ethical restrictions.

Ethical Approval

All studies were approved by the Baltic AI Research University Ethics Committee (protocol BAIRU-EC-2022-0164) and conducted in accordance with the Declaration of Helsinki. All participants provided written informed consent. The ACL risk cohort study was additionally approved by the respective university athletic departments.

Appendix A

DL-MSK Architecture and Training Configuration

This appendix provides the complete DL-MSK architecture specification, training hyperparameters, physics consistency loss formulation, and per-variable accuracy breakdown across the three clinical cohorts.

A.1 Network Architecture

1a. Input: 17 IMUs x 6 DOF (3 accel + 3 gyro) x 240 Hz = 102-channel temporal signal; window 120 frames (0.5 s)

1b. Temporal encoder: 4 dilated causal conv layers (dilations 1,2,4,8; 64 filters; kernel 7; residual; BatchNorm + ELU)

2a. Cross-sensor attention: 8 heads, d_k 32, operating across the 17-sensor dimension at each time step

2b. Anthropometric conditioning: FiLM layer -- height, mass, segment lengths modulate encoder features via affine transform

3a. Output heads: Kinematics (23 joint angles), Kinetics (9 joint moments: hip/knee/ankle x 3 planes), Muscle forces (92 muscles)

3b. Physics loss: $\|M_{\text{predicted}} - J^T * F_{\text{muscle}}\|^2$ where J is the moment arm Jacobian from OpenSim generic model ($\lambda = 0.1$)

A.2 Training Configuration

4a. Optimiser: AdamW (lr $5e-4$, weight decay $1e-3$); cosine annealing with 10-epoch warmup

4b. Loss: MSE(kinematics) + MSE(kinetics) + MSE(muscle forces) + 0.1 * physics_consistency; equal task weighting

5a. Validation: leave-one-subject-out cross-validation (per cohort); best model by validation RMSE on kinetics

5b. Augmentation: Gaussian noise ($\sigma = 0.02 \times \text{SD}$ per channel), random temporal shift (± 5 frames), sensor dropout ($p = 0.05$)

6a. Hardware: single NVIDIA RTX 3090; training 4.2 h per fold (OA cohort); inference 8 ms per frame (real-time at 125 Hz)

6b. Total parameters: 3.8 M (encoder 2.4 M + attention 0.6 M + heads 0.8 M)