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AI Biomechanics Analysis Software: Technological Foundations, Mechanical Interpretation, and Practical Applications

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Abstract

Artificial intelligence is rapidly transforming the way human movement is analysed across sports science, rehabilitation, and clinical biomechanics. Traditional motion analysis has historically depended on laboratory-based instrumentation including marker-based motion capture systems, force platforms, and electromyography, which, while highly accurate, remain expensive and difficult to deploy in real-world environments. The emergence of AI-based biomechanics analysis software—integrating computer vision, machine learning, and real-time motion tracking—has enabled markerless movement analysis using standard video inputs.

This article examines the technological foundations, mechanical interpretation, and practical applications of AI-driven movement analysis systems within contemporary biomechanics. Particular emphasis is placed on the translation of AI-derived kinematic data into meaningful mechanical insights through principles such as force vector orientation, torque distribution, load transfer pathways, and kinetic chain coordination within the MMSx mechanical framework. The article further evaluates the clinical and performance implications of real-time movement feedback, discusses reliability and validation challenges associated with markerless analysis, and outlines the future integration of multimodal sensing technologies including wearable sensors and force-detection systems.

AI biomechanics software has the potential to significantly expand access to movement science by enabling scalable, ecologically valid biomechanical assessment outside laboratory settings. However, the scientific and clinical value of these systems ultimately depends on rigorous validation, transparent methodological limitations, and integration with established biomechanical principles governing human movement.

This article examines the technological foundations of AI-based biomechanics systems, explains their interpretation through mechanical principles, and discusses applications, limitations, and future directions in movement science.

Keywords:

Artificial Intelligence, Biomechanics, Markerless Motion Capture, Pose Estimation,

Movement Mechanics, Sports Biomechanics, Rehabilitation Technology

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Introduction

The scientific analysis of human movement has long occupied a central position within biomechanics, sports science, and clinical rehabilitation. Understanding how the musculoskeletal system generates and transmits forces during dynamic activity is fundamental to improving athletic performance, preventing injury, and guiding therapeutic intervention. For decades, the investigation of human movement mechanics has relied on laboratory-based measurement technologies such as marker-based motion capture systems, force platforms, and electromyographic analysis. These tools have enabled detailed measurement of joint kinematics, ground reaction forces, and muscle activation patterns, providing valuable insight into the mechanical determinants of human movement.

Despite their scientific value, traditional biomechanical assessment systems remain limited in accessibility and ecological validity. Motion capture laboratories require specialised equipment, controlled environments, and trained technical personnel, which restricts their availability to research institutions and elite performance centres. As a result, most athletes, patients, and practitioners operate outside environments where comprehensive biomechanical analysis can be routinely applied. This disconnect between laboratory measurement capability and real-world movement environments has been widely recognised as one of the major limitations of contemporary biomechanics practice.

Recent advances in artificial intelligence, computer vision, and machine learning have begun to transform this landscape. Markerless motion capture technologies driven by deep learning algorithms now enable the estimation of human joint positions and segment orientations directly from video data captured by standard camera systems. These technologies have introduced the possibility of performing biomechanical analysis in environments previously inaccessible to laboratory instrumentation, including sports training facilities, rehabilitation clinics, and field-based performance settings. By automating the extraction of kinematic information from visual data streams, AI-driven biomechanics platforms have the potential to dramatically expand the scale at which movement analysis can be conducted.

However, the emergence of artificial intelligence in biomechanics introduces a critical conceptual challenge: the distinction between **kinematic observation and mechanical interpretation**. While AI systems are increasingly capable of detecting joint angles, segment trajectories, and movement asymmetries with high accuracy, these measurements alone do not fully explain the mechanical forces acting within the musculoskeletal system. Movement mechanics is fundamentally governed by the interaction between force vectors, joint torques, and load transfer pathways across the kinetic chain. Without interpretation within this mechanical context, purely kinematic descriptions risk overlooking the underlying causes of movement inefficiency and tissue loading.

The **MMSx (Movement Mechanics & Biomechanics Science) framework** addresses this challenge by interpreting movement through a mechanical decision-science perspective. Within this framework, human motion is conceptualised as a system of force regulation, torque distribution, and kinetic chain coordination operating under the constraints of gravity and task demands. Artificial intelligence therefore serves not merely as a descriptive tool for motion tracking but as a computational extension of biomechanical reasoning, assisting practitioners in identifying movement patterns that influence force transmission and musculoskeletal loading.

The purpose of this article is to examine the emerging role of **AI biomechanics analysis software** within modern movement science. Specifically, the article explores the technological foundations of AI-driven motion analysis, the translation of kinematic data into mechanical insight, and the implications of real-time biomechanical feedback for sports performance and clinical rehabilitation. In addition, the paper discusses methodological limitations associated with markerless motion analysis and outlines the future integration of multimodal sensing technologies capable of enhancing the accuracy and interpretive power of AI-based biomechanical systems.

By situating artificial intelligence within established mechanical principles of human movement, the article aims to clarify how AI technologies can support evidence-based decision making in biomechanics while maintaining the scientific rigour required for meaningful clinical and performance applications.

The biomechanical study of human movement has historically been constrained by the tools available to practitioners and researchers. For much of the twentieth century, the analysis of gait, posture, and athletic technique relied on trained eye observation supplemented by rudimentary two-dimensional video. Observers would annotate joint angles, estimate ground reaction forces, and draw qualitative inferences from footage that was, by any modern standard, coarse and temporally imprecise. Even as the discipline matured, the prevailing paradigm remained one of expert interpretation—an inherently subjective and labour-intensive process prone to inter-rater variability.

The transition to digital biomechanics laboratories in the 1990s and early 2000s introduced three-dimensional motion capture systems, force platforms, and electromyographic recording, collectively enabling a level of kinematic and kinetic resolution that was genuinely transformative. Yet these systems carried their own constraints: prohibitive capital costs, restrictive environmental requirements, and extended processing pipelines that rendered real-time feedback largely impractical outside specialised research contexts. A competitive sprinter, a post-surgical rehabilitation patient, or a youth athlete in a community gym was unlikely ever to receive the depth of movement analysis that such infrastructure could provide.

The contemporary emergence of artificial intelligence—and specifically the convergence of computer vision, machine learning, and edge computing—has introduced a genuinely new trajectory for the field. AI biomechanics analysis software represents not merely an incremental improvement on existing tools, but a structural reconfiguration of who can access movement science, when it can be applied, and what volume of data can be meaningfully interpreted. Understanding the scope, the underlying architecture, and the practical implications of this shift is essential for sports scientists, clinicians, and performance coaches operating at the leading edge of evidence-based practice.

The Limitations of Traditional Motion Analysis Environments

Conventional three-dimensional motion analysis requires a controlled laboratory setting in which retroreflective markers are affixed to anatomical landmarks on the participant's body. A network of infrared cameras—typically eight to twelve in number—triangulates marker position in three-dimensional space at sampling rates that may reach two hundred or more frames per second. While the kinematic fidelity achievable through this methodology is exceptional, the ecological validity of laboratory-based assessment is persistently questioned.

Human movement, particularly in sport and occupational contexts, is inherently reactive and unpredictable. The biomechanics of a defensive cutting manoeuvre executed under competitive pressure differs meaningfully from the same movement performed in a sterile laboratory environment with an observer present. Force-plate based analyses, similarly, capture discrete footfalls during straight-line or minimally constrained tasks, rarely approximating the multi-directional, contact-laden demands of real-world athletic performance.

The resource requirements associated with laboratory-based analysis further limit its clinical and coaching applications. Setup and marker placement typically requires thirty to sixty minutes per session; post-processing of raw motion data is a specialised task demanding significant analyst time; and the resulting datasets—while rich—are often reduced to summary statistics that obscure the temporal dynamics of movement. The bottleneck between data collection and actionable output has historically been the practitioner's time and interpretive capacity, not the resolution of the measurement instrument.

The bottleneck in biomechanical assessment has never been sensor resolution—it has been the human capacity to interpret movement at scale, in real time, under ecologically valid conditions.

Table 1: Comparison of Traditional vs. AI-Driven Biomechanics Analysis Systems

Aspect	Traditional Marker-Based Systems	AI-Driven Markerless Systems (e.g., OpenPose, MediaPipe, Theia3D)	Key Advantages of AI Systems	Key Limitations of AI Systems
Environment Required	Controlled laboratory, infrared cameras, markers	Standard RGB video, field/clinic/sports settings	High ecological validity, scalable deployment	Sensitive to lighting, occlusion, clothing
Setup Time	30–60 minutes per session (marker placement)	Minimal (camera positioning only)	Real-time capability	Potential session-to-session variance
Kinematic Accuracy (Sagittal Plane)	Gold standard (errors <1–2°)	3–8° MAE for hip/knee flexion; 2–5° in controlled gait	Good for functional tasks	Degrades in multi-planar/high-velocity movements

Kinetic Estimation	Direct force platforms + inverse dynamics	Inferred from acceleration (F=ma); torque via moment arms (τ=r×F)	Indirect but scalable	Approximations only; requires fusion for precision
Cost & Accessibility	High capital, specialized personnel	Low-cost hardware, edge computing	Democratizes access	Validation envelope narrower than lab systems
Real-Time Feedback	Limited (post-processing dominant)	Enabled (concurrent cues)	Enhances motor learning	Dependent on processing latency

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Core Technologies Underpinning AI Biomechanics Systems

Contemporary AI biomechanics platforms integrate three broad technological domains: computer vision, motion tracking algorithms, and machine learning pattern detection. These components are architecturally interdependent, and their combined operation enables a degree of analytical capability that no single technology could achieve in isolation.

Computer vision refers to the capacity of algorithms to extract meaningful structural information from raw image or video data. In the context of biomechanics, this encompasses the detection of human body segments, the estimation of joint positions, and the reconstruction of skeletal geometry from two-dimensional or three-dimensional imaging inputs. The development of deep convolutional neural networks trained on large-scale human pose datasets—most notably models derived from the COCO and Human3.6M benchmarks—has enabled pose estimation algorithms to achieve clinically relevant accuracy from standard camera hardware. Systems such as OpenPose, MediaPipe BlazePose, and more recent transformer-based architectures can localise thirty-three or more anatomical keypoints at speeds consistent with real-time processing on consumer-grade graphics hardware.

Motion tracking extends pose estimation across time, enabling the derivation of angular kinematics, segment velocities, and acceleration profiles from sequential frame data. Robust tracking must account for occlusion, rapid segment displacement, variable lighting conditions, and the non-rigid nature of soft tissue relative to underlying skeletal structure. Kalman filtering, optical flow estimation, and attention-based temporal modelling have each been applied to these challenges, with ensemble approaches demonstrating superior robustness in unconstrained environments. The integration of depth cameras—structured light or time-of-flight sensors—further enhances three-dimensional reconstruction accuracy without the marker-dependency of laboratory systems.

Machine learning pattern detection operates on the kinematic and kinetic data streams produced by the preceding pipeline. Supervised classification models trained on labelled movement datasets can identify specific technique deviations, flag asymmetries relative to normative populations, and classify movement quality scores with interclass correlation coefficients that approach those of expert human raters for well-defined tasks. Unsupervised and semi-supervised approaches are increasingly applied to the discovery of movement patterns not predefined by researchers, enabling exploratory identification of compensatory mechanics that may precede clinically overt dysfunction.

Figure 1. AI biomechanics analysis workflow

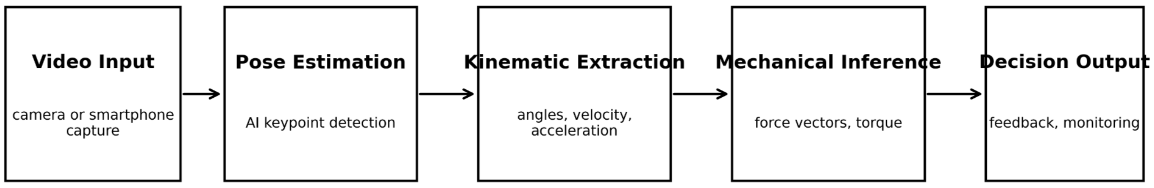


Figure 1: Conceptual pipeline illustrating the progression from video capture to pose estimation, kinematic extraction, mechanical inference, and applied decision outputs in AI-based movement analysis systems.

Recent advances in deep-learning-based pose estimation models such as OpenPose and MediaPipe have enabled markerless movement tracking using standard camera systems (11–18).

Mechanical Foundations: Linking AI Kinematics to Mechanical Loading

While artificial intelligence systems in biomechanics primarily extract **kinematic information**—joint positions, segment trajectories, angular velocities, and movement symmetry—the interpretation of human movement ultimately requires translation of these observations into **mechanical loading variables**. Kinematics describes how the body moves; biomechanics explains **why that movement occurs and what forces the tissues experience**.

Within the MMSx framework, AI-derived movement data must therefore be interpreted through fundamental mechanical relationships that govern musculoskeletal loading. Two foundational equations are particularly relevant when translating visual movement information into mechanical insight.

The first is the **Newtonian force equation**:

$$F = ma$$

This equation explains that force is produced when a mass is accelerated, forming the basis of movement and external loading in biomechanics.

This relationship describes how the forces acting on a body segment are determined by its mass and acceleration. In the context of AI-based movement analysis, acceleration values derived from sequential pose estimation frames allow approximate estimation of the forces required to produce observed motion. When an athlete rapidly decelerates during a landing task or changes direction during cutting movements, the acceleration profiles derived from AI kinematics provide indirect insight into the magnitude of forces transmitted through the lower extremity and trunk.

The second fundamental relationship governing movement mechanics is the **torque equation**, which describes the rotational effect of a force acting at a distance from a joint center:

$$\tau = r \times F$$

This equation shows that joint torque is created when a force acts through a moment arm around a joint axis.

Here, τ\tauτ represents joint torque, rrr represents the moment arm (the perpendicular distance between the joint center and the applied force vector), and FFF represents the magnitude of the applied force. In human movement, torque generation determines how muscles and connective tissues must act to rotate segments around joints during dynamic activity.

AI-based pose estimation systems provide the spatial coordinates necessary to approximate joint centers and segment orientations, allowing estimation of moment arms during movement. When combined with estimated external forces—such as ground reaction forces inferred from acceleration or wearable sensors—these kinematic inputs can be translated into approximations of joint torque distribution.

Within applied biomechanics contexts, this mechanical translation has important implications. A visually subtle deviation such as increased trunk lean during squatting may substantially increase the moment arm of the load relative to the lumbar spine, thereby elevating spinal torque demands even if the joint angle deviation appears minor. Similarly, a small increase in knee valgus during landing can alter the moment arm of ground reaction forces relative to the knee joint center, increasing ligamentous loading and potential injury risk.

For this reason, AI-based biomechanics systems should not be interpreted solely as tools for measuring movement geometry. Their practical value lies in their capacity to infer the **mechanical consequences of observed movement patterns**—specifically how force vectors, moment arms, and accelerations interact to determine joint loading conditions.

Within the MMSx mechanical decision-science framework, the purpose of AI movement analysis is therefore to bridge the gap between **observable kinematics and underlying mechanical loading**, enabling practitioners to identify movement patterns that alter force distribution, torque demands, and kinetic chain stability during dynamic activity.

Table2: Key Mechanical Parameters Interpreted via MMSx Framework from AI Kinematics

Mechanical Parameter	**AI-Derived Input**	**Equation/Computation**	**Clinical/Performance Insight**	**Example Deviation & Implication**
Net Force on Segment	Acceleration from trajectories	F = ma	Estimates loading during deceleration/landing	High a → elevated GRF inference → injury risk

Joint Torque	Moment arm + estimated force	$\tau = r \times F$	Quantifies rotational demand on muscles/ligaments	Increased knee τ in valgus → ACL stress
Force Vector Orientation	Segment orientation + CoM	Vector relative to joint centers	Identifies inefficient load paths	Trunk lean → posterior shift → lumbar overload
Load Transfer Pathway	Multi-segment coordination	Sequential force propagation	Detects kinetic chain disruptions	Delayed hip extension → compensatory knee stress
Shear vs. Compression	Joint angle + velocity/acceleration	Inferred from orientation/shear components	Assesses ligament vs. cartilage loading	Excessive shear in cutting → ligament strain

EQUATIONS:

Torque equation

$$\tau = r \times F$$

This equation shows that joint torque is created when a force acts through a moment arm around a joint axis.

Force equation

$$F = ma$$

This equation explains that force is produced when a mass is accelerated, forming the basis of movement and external loading in biomechanics.

Work equation

$$W = F \cdot d$$

This equation describes mechanical work as the force applied through a displacement in the direction of movement.

Power equation

$$P = \frac{W}{t}$$

This equation defines power as the rate at which mechanical work is performed over time.

References: 1–3, 36–38

Momentum equation

$$p = mv$$

This equation explains linear momentum as the quantity of motion created by the interaction of mass and velocity.

Angular momentum equation

$$L = I\omega$$

This equation describes angular momentum as rotational motion determined by moment of inertia and angular velocity.

Impulse equation

$$J = F\Delta t$$

This equation explains impulse as the effect of force applied over time, producing a change in momentum.

Center of Mass equation

$$COM = \frac{\sum m_i x_i}{\sum m_i}$$

This equation calculates the center of mass as the weighted average position of all body segments.

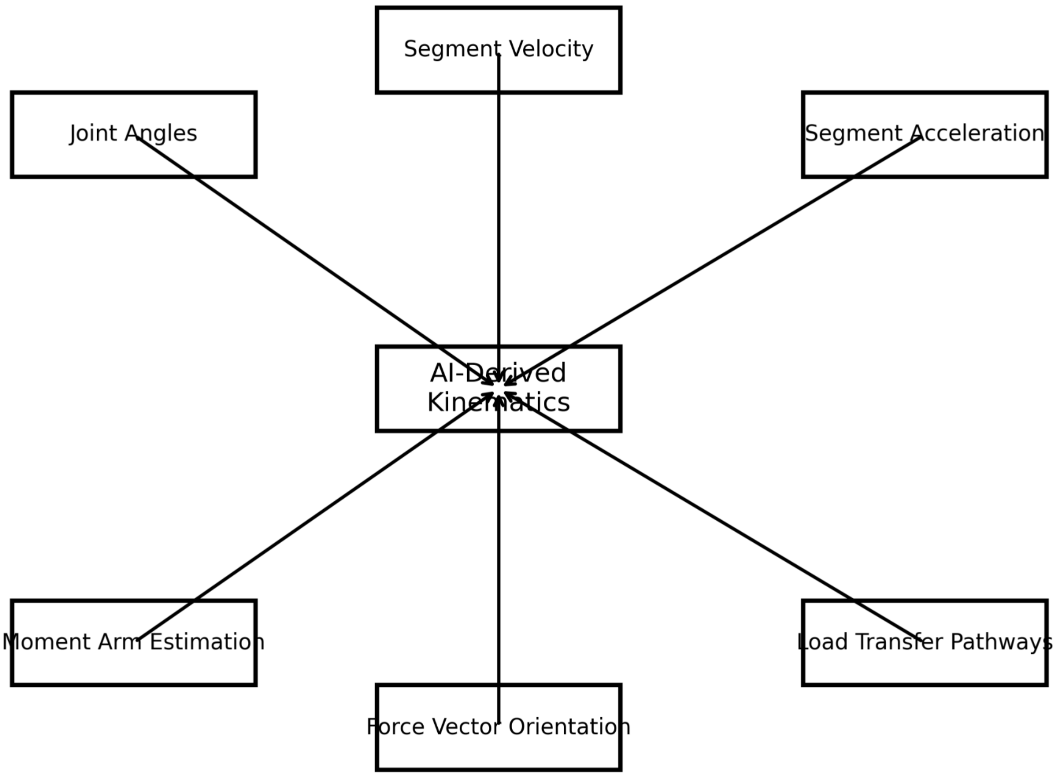


Figure 4. Mechanical variables derived from AI-based movement analysis.

Conceptual model illustrating how AI-derived kinematic outputs (joint angles, segment velocity, and acceleration) are translated into mechanically relevant variables including moment arm estimation, force vector orientation, and load transfer pathways within biomechanical interpretation.

AI Interpretation within the MMSx Mechanical Framework

AI-based movement analysis systems primarily generate kinematic outputs such as joint coordinates and segment trajectories. However, positional tracking alone does not describe the mechanical loading experienced by the musculoskeletal system. Within the MMSx mechanical framework, kinematic data must be interpreted through mechanical variables including force vectors, torque distribution, load transfer pathways, and shear versus compression dynamics to understand movement mechanics and injury risk.

Artificial intelligence applied to human movement analysis must ultimately extend beyond surface-level kinematic description. While computer vision systems can accurately identify joint positions, segment angles, and movement trajectories, these measurements alone do not fully describe the mechanical processes governing musculoskeletal loading. Within the MMSx (Movement Mechanics & Biomechanics Science) framework, AI-based movement analysis is interpreted through the lens of mechanical decision-science, in which movement is understood primarily as a system of force generation, transmission, and regulation across the human kinetic chain.

In this model, artificial intelligence functions as a computational observer capable of identifying patterns within motion data that correspond to underlying mechanical states of the musculoskeletal system. Rather than evaluating movement solely against idealised postural templates, the MMSx approach prioritises analysis of how forces propagate through the body during dynamic activity and how mechanical efficiency or inefficiency emerges from the interaction of anatomical structures under load.

A central component of this interpretation is the orientation of force vectors relative to the body's joint centres. During locomotion, lifting, or sport-specific actions, the ground reaction force vector interacts with joint centres and segment moment arms to determine the mechanical demands placed on muscles, ligaments, and articular cartilage. AI systems capable of tracking body segment orientation across time can estimate how these force vectors shift during movement execution, allowing practitioners to identify deviations that alter joint loading patterns. For example, excessive trunk inclination during squatting or asymmetrical ground contact during running can redirect force vectors in ways that increase joint moments and tissue stress.

Closely related to vector orientation is the concept of torque distribution across joints. Torque represents the rotational effect of force acting at a distance from a joint centre and is one of the primary determinants of musculoskeletal loading during dynamic movement. Within the MMSx framework, AI-derived kinematic data is interpreted in terms of how torque demands are distributed between proximal and distal segments. Disruptions in torque sharing—such as excessive knee torque during landing due to insufficient hip contribution—represent a key mechanical signature of inefficient movement patterns and elevated injury risk.

The MMSx approach further emphasises the importance of load transfer pathways within the kinetic chain. Human movement is not produced by isolated joints acting independently but by coordinated interactions among multiple segments that transmit mechanical energy throughout the body. Efficient movement depends on the orderly propagation of forces through these pathways, from the ground interface through the lower extremity, pelvis, trunk, and upper body when required by the task. AI systems analysing sequential motion data can detect interruptions in these pathways, such as delayed hip extension during lifting or asymmetrical pelvic rotation during gait, both of which may redistribute mechanical stress to adjacent joints.

Another critical mechanical consideration is the balance between shear and compressive loading across articular structures. While compressive forces are often well tolerated by joint surfaces due to their distribution across cartilage and subchondral bone, excessive shear forces may place greater strain on ligaments and connective tissues responsible for stabilising joint motion. AI-assisted analysis that identifies changes in joint orientation, segment velocity, or directional acceleration can help infer conditions under which shear loading may increase relative to compression. Such information is particularly relevant in high-velocity or change-of-direction activities where joint stability depends on precise neuromuscular coordination.

Finally, the MMSx framework recognises that the integrity of the kinetic chain is central to movement efficiency and injury resilience. Coordination among segments determines whether mechanical energy is transmitted smoothly through the system or dissipated through compensatory strategies. AI-driven analysis of multi-segment coordination patterns can reveal disruptions in this chain, such as asynchronous hip-knee extension during jumping or inadequate trunk stabilisation during unilateral tasks. These patterns often represent early indicators of fatigue, neuromuscular inhibition, or structural limitation.

Within the MMSx paradigm, artificial intelligence therefore serves not merely as a descriptive tool but as a computational extension of biomechanical reasoning. By integrating kinematic observation with mechanical interpretation—force vectors, torque distribution, load transfer, shear-compression balance, and kinetic chain coordination—AI systems can assist practitioners in identifying movement patterns that influence musculoskeletal loading and long-term tissue health. The objective is not to replace expert clinical or coaching judgement but to augment it with scalable, data-driven insight into the mechanical determinants of human movement.

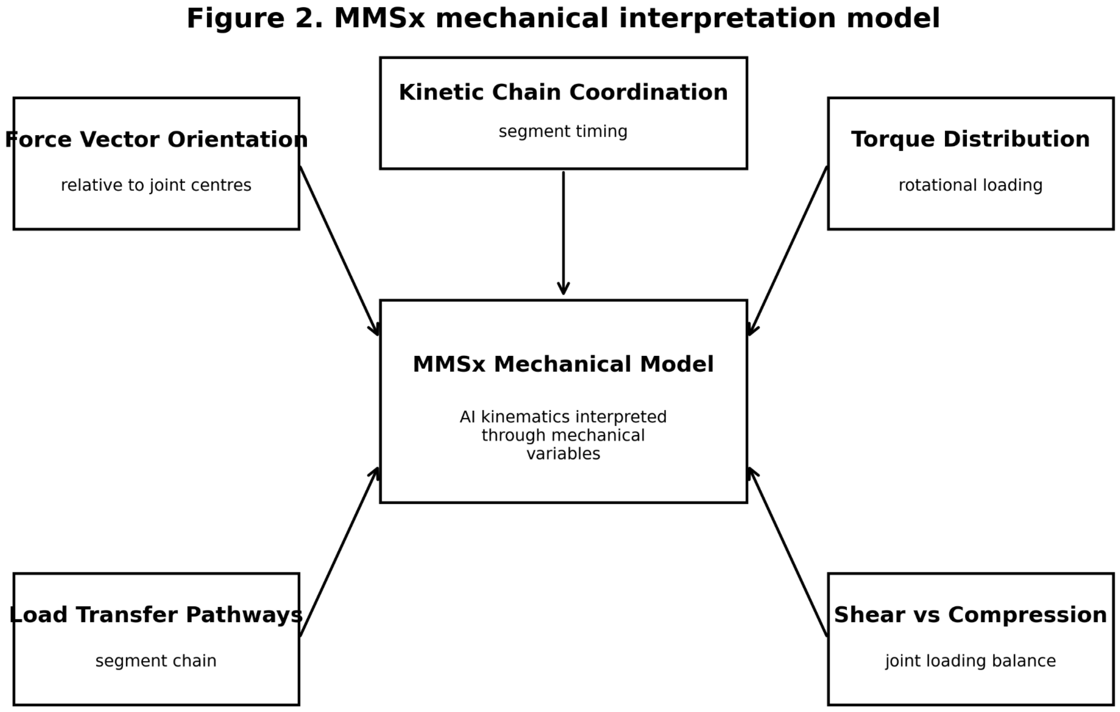


Figure 2: Schematic representation of the principal mechanical domains through which AI-derived movement data are interpreted within the MMSx framework, including force vector orientation, torque distribution, kinetic chain coordination, load transfer pathways, and shear versus compression dynamics.

REFERENCES: 32–35, 7, 8, 36

Real-Time Analysis: Implications for Coaching and Clinical Practice

Perhaps the most consequential practical shift enabled by AI biomechanics systems is the capacity for real-time movement feedback. Laboratory-based analysis has traditionally operated within an asynchronous paradigm: data is collected during one session and interpreted for delivery in a subsequent consultation. The temporal gap between movement execution and corrective feedback has implications for motor learning; contemporary neuroscience of skill acquisition consistently identifies concurrent or immediately terminal augmented feedback as more effective for early-stage motor skill development than delayed feedback paradigms.

AI systems capable of detecting kinematic deviations—such as excessive contralateral trunk lean during unilateral loading, dynamic knee valgus under eccentric stress, or forward head carriage during overhead pressing movements—and communicating those deviations to the athlete or patient within the same training repetition represent a meaningful advancement in the feedback-motor learning cycle. Early implementations of real-time coaching cues have demonstrated measurable improvements in movement quality metrics over short training blocks, with some intervention studies reporting significant reductions in knee abduction moment during landing tasks following AI-guided feedback protocols.

For clinical rehabilitation, real-time biomechanical monitoring addresses a persistent gap between the controlled conditions of a physiotherapy session and the unmonitored environment in which patients perform home exercise programmes. Wearable and camera-based AI monitoring systems provide clinicians with objective compliance and quality data across the entirety of a rehabilitation programme, enabling data-driven progression decisions that are not dependent solely on the therapist's in-session observation.

Mechanical energy principles provide an additional framework for understanding movement efficiency and performance during athletic tasks.

Kinetic energy

$$KE = \frac{1}{2}mv^2$$

This equation defines kinetic energy as the energy a body possesses because of its motion.

Potential energy

$$PE = mgh$$

This equation defines potential energy as the stored energy a body has due to its height against gravity.

Total mechanical energy

$$E = KE + PE$$

This equation shows total mechanical energy as the sum of kinetic and potential energy during movement.

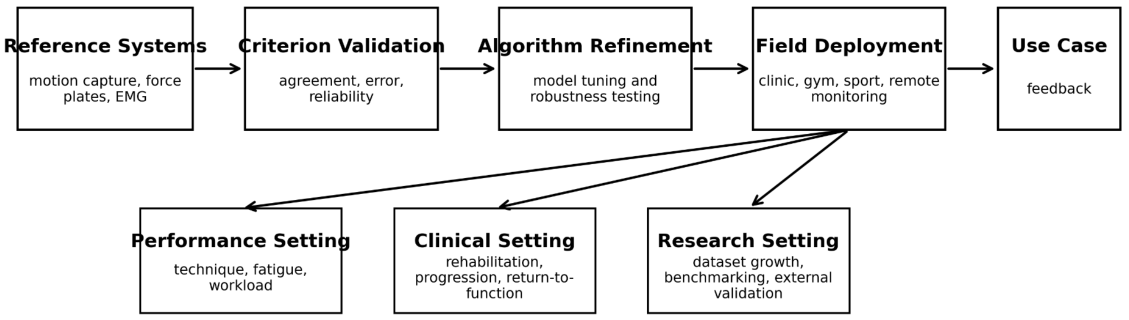
Data Reliability, Validation, and the Question of Clinical Translation

The clinical and scientific credibility of AI biomechanics systems depends fundamentally on the rigour with which their outputs have been validated against established reference standards. The movement science literature contains a growing body of criterion validity studies comparing AI pose estimation outputs with simultaneous laboratory-based motion capture data. The results are broadly encouraging for sagittal-plane kinematics assessed under controlled conditions—joint angle estimates from monocular camera systems have demonstrated mean absolute errors in the range of three to eight degrees relative to marker-based reference measurements for knee and hip flexion during common functional movements.

Validity coefficients degrade, however, under conditions of rapid multi-planar movement, deep joint flexion angles, significant adipose tissue coverage of bony landmarks, and lateral or posterior camera positions that introduce anatomical landmark occlusion. These constraints are not trivial in applied performance or clinical settings; they represent precisely the conditions under which biomechanical analysis is most diagnostically valuable. The scientific community has an obligation to communicate these limitations transparently, and practitioners adopting AI analysis tools must develop the critical literacy to interpret platform outputs in the context of the validated performance envelope of each system.

Repeatability and inter-session reliability present additional methodological considerations. Unlike marker-based systems where landmark placement protocols can be standardised across sessions, the anatomical keypoint estimates derived from AI systems may exhibit session-to-session variance attributable to variation in clothing, camera positioning, ambient lighting, and background complexity. Rigorous implementation protocols addressing these variables are a prerequisite for longitudinal monitoring applications in which the detection of true change must be discriminated from measurement noise.

Figure 3. Validation and deployment pathway for AI biomechanics systems



Translational pathway from laboratory reference validation to applied deployment across performance, clinical, and research environments.

Figure 3: Translational workflow showing the progression from laboratory reference validation and algorithm refinement to applied deployment across performance, clinical, and research environments.

References: 14–24

Limitations of AI-Based Biomechanics Analysis Systems

Despite the rapid advancement of artificial intelligence in human movement analysis, several methodological limitations must be recognised when interpreting AI-derived biomechanical data. Awareness of these constraints is essential to ensure that computational outputs are applied appropriately within clinical and performance environments.

One major challenge arises from **camera occlusion**, in which anatomical landmarks become temporarily hidden from the visual field of the camera. Occlusion may occur when body segments overlap during movement, when external objects obstruct the view, or when multiple individuals occupy the frame simultaneously. When occlusion occurs, pose estimation algorithms must rely on predictive modelling to infer landmark position, which may introduce estimation error in joint angle calculations.

A second limitation involves **clothing artifacts**. AI pose estimation systems identify skeletal landmarks by analysing visual features associated with human body contours. Loose clothing, compression garments, reflective materials, or layered apparel can alter the visual representation of anatomical landmarks, potentially affecting the accuracy of joint position detection. These artifacts may lead to small but meaningful deviations in calculated joint angles, particularly in movements involving rapid segment displacement.

Deep joint flexion represents another known challenge for camera-based motion analysis systems. During movements such as deep squatting, lunging, or seated transitions, anatomical landmarks may become partially obscured or visually compressed from the perspective of the camera. This geometric distortion can reduce the accuracy of landmark localisation, particularly for the hip and knee joints when viewed from non-optimal camera angles.

AI biomechanics systems may also encounter difficulties during **multi-planar or high-velocity movements**. Many pose estimation algorithms demonstrate strong accuracy for sagittal-plane movements such as walking or squatting under controlled conditions. However, complex athletic movements—including rapid changes of direction, rotational tasks, or contact-based sport actions—introduce additional challenges related to motion blur, rapid segment acceleration, and non-linear joint trajectories. These conditions may increase tracking error and reduce the precision of derived kinematic variables.

Environmental factors can further influence system reliability. Variations in lighting conditions, camera resolution, background complexity, and camera positioning may affect the performance of computer vision models responsible for anatomical landmark detection.

For these reasons, AI-based movement analysis should be interpreted as an **approximation of biomechanical behaviour rather than a direct measurement of internal mechanical forces**. Validation against established reference systems—such as three-dimensional motion capture, force platforms, electromyography, and musculoskeletal simulation models—remains essential for confirming the accuracy and reliability of AI-derived outputs.

Within the MMSx framework, artificial intelligence is therefore viewed as a **decision-support tool that enhances observational capacity**, rather than a replacement for biomechanical reasoning or practitioner expertise. When applied with appropriate methodological awareness and validation, AI-based analysis systems hold significant potential to expand the accessibility and scale of biomechanical assessment across clinical, athletic, and research environments.

Table 3: Representative Validation Metrics for Markerless Pose Estimation in Biomechanics (from Literature Aligned with Article References)

Model/System	**Task/Movement**	**Joint(s) Assessed**	**Metric**	**Value (Typical Range)**	**Comparison Standard**	**Notes (from Validation Studies)**
OpenPose/MediaPipe	Gait, Squat, DVJ	Knee Flexion/Extension	MAE	2.3–4.1°	Marker-based (Vicon/Qualisys)	Better on camera side; sagittal plane strongest
OpenPose/MediaPipe	Gait	Hip/Knee/Ankle	ICC (1,3)	0.89–0.99	3D Motion Capture	Excellent waveform similarity (CMC 0.89–0.994)

OpenPose/MediaPipe	Shoulder Abduction	Shoulder ROM	MAE	1.97–7.42° (distance-dependent)	Goniometer/MoCap	Excellent reliability (ICC >0.81)
Theia3D	Gait/Running	Lower Limb (Sagittal)	RMSD	<6° (hip/knee); 6–14° (hip offset)	Marker-based	Excellent for spatiotemporal; moderate pelvic tilt
General Markerless	Functional Tasks	Knee Valgus	MAE	2.4–3.2°	3D Marker-based/Human	Comparable to human raters; strong correlation (r=0.97)

Limitations of AI Systems

- **lighting variation affecting pose detection**
- **camera calibration and perspective distortion**

REFERENCES: 19–24

The Integration Horizon: Wearables, Performance Analytics, and Multimodal Fusion

The next developmental frontier for AI biomechanics software is the integration of camera-based kinematic data with complementary data streams from inertial measurement units, force-sensing insoles, physiological monitors, and environmental sensors. This multimodal fusion approach addresses a fundamental limitation of any single sensing modality: no individual sensor type captures the full biomechanical and physiological context of human movement.

Inertial measurement units worn at the limb segments or lumbar spine provide continuous kinematic data in field environments where camera coverage is impractical, while force-sensing insoles offer ground reaction force surrogates that complement the kinematic picture with kinetic information. The integration of these streams with AI-derived pose data creates a composite movement profile of substantially greater diagnostic power than any component individually. Machine learning frameworks capable of learning from heterogeneous multimodal inputs are central to realising this potential, and current research in sensor fusion for human motion analysis is advancing rapidly.

Performance analytics platforms represent the longitudinal application layer of this technology stack. Individual session data, accumulated across training cycles and competitive seasons, provides the temporal depth required to identify gradual kinematic drift, fatigue-induced technique deterioration, and the emergence of compensatory movement patterns in the weeks preceding injury. Population-level datasets—when appropriately de-identified and aggregated—offer the statistical power necessary to build predictive models of injury risk and performance plateau that would be unachievable from individual case data alone.

The direction of travel for AI biomechanics software is, in aggregate, toward a system capable of continuous, ecologically valid, quantitatively rigorous movement surveillance integrated into the practitioner's everyday workflow without specialist infrastructure requirements. The distance between current capability and that vision is measurable, and the trajectory of development in computer vision, edge computing, and applied machine learning suggests it is a practical rather than speculative destination. The obligation of the movement science community is to ensure that this development is guided by scientific rigour, clinical utility, and an uncompromising commitment to validation standards.

Conclusion

Artificial intelligence is reshaping the landscape of biomechanics by extending movement analysis beyond the laboratory and into ecologically valid clinical, athletic, and real-world performance environments. The significance of AI biomechanics software lies not merely in its ability to automate pose estimation or track joint motion, but in its potential to translate kinematic information into mechanically meaningful interpretations of force distribution, torque demand, and kinetic chain behaviour.

Within the MMSx framework, the value of AI is therefore not descriptive alone but interpretive. Human movement must be understood as a force-regulated mechanical system, and AI becomes most useful when it assists practitioners in identifying deviations that alter load transfer, stability, and tissue stress under dynamic conditions. This perspective moves the discussion beyond digital convenience and toward genuine biomechanical decision support.

At the same time, the scientific utility of AI-based biomechanics systems depends on rigorous validation, transparent recognition of methodological limitations, and appropriate integration with practitioner expertise. Markerless analysis, multimodal sensing, and machine learning prediction models offer major opportunities, but their outputs must remain anchored to established principles of mechanics and clinical reasoning.

AI biomechanics software should therefore be understood not as a replacement for biomechanical science, but as an emerging extension of it—one that, if developed and applied rigorously, may significantly enhance the scale, accessibility, and practical utility of movement analysis across sports science, rehabilitation, and human performance.

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