RESEARCH PAPER

Artificial Intelligence in Osteoarthritis Pain Management: Current Applications and Future Perspectives

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Abstract

Osteoarthritis (OA) is the most prevalent joint disorder worldwide and a leading cause of chronic pain, disability, and reduced quality of life. Despite advances in imaging and clinical management, substantial heterogeneity exists in symptom severity, disease progression, and treatment response. Artificial intelligence (AI) has emerged as a promising technology capable of improving diagnostic accuracy, predicting pain trajectories, and supporting personalized treatment decisions. Machine learning and deep learning algorithms can analyze large-scale imaging, clinical, and patient-reported datasets to identify complex disease patterns that are often undetectable through conventional approaches. Recent advances in explainable AI and multimodal learning have further enhanced the potential clinical applicability of these technologies. This mini-review summarizes current applications of AI in osteoarthritis pain management, including diagnostic imaging, pain prediction, rehabilitation planning, and surgical decision-making. Current limitations and future directions for precision musculoskeletal medicine are also discussed.

Keywords: osteoarthritis, artificial intelligence, chronic pain, machine learning, deep learning, precision medicine

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Introduction

Osteoarthritis is a chronic degenerative joint disease characterized by progressive cartilage deterioration, subchondral bone remodeling, synovial inflammation, and chronic pain. It affects more than 500 million people worldwide and represents one of the most important causes of disability among older adults. [1,2]

Pain remains the principal symptom of OA and is responsible for most healthcare consultations. However, the relationship between structural joint abnormalities and symptom severity is often inconsistent. Patients with similar radiographic findings may report markedly different pain experiences, suggesting that conventional imaging alone is insufficient to fully characterize disease burden.

Artificial intelligence has emerged as a transformative technology in healthcare. Recent developments in machine learning (ML), deep learning (DL), and natural language processing (NLP) have enabled analysis of large multidimensional datasets, creating opportunities for improved diagnosis, risk stratification, and personalized management. [3,4]

This mini-review summarizes recent advances in AI applications relevant to osteoarthritis pain management and discusses future opportunities for precision musculoskeletal care.

Literature Search Strategy

A narrative literature review was performed using PubMed, Scopus, and Google Scholar. Articles published between January 2020 and March 2025 were identified using combinations of the terms “osteoarthritis,” “artificial intelligence,” “machine learning,” “deep learning,” “pain prediction,” “MRI,” “radiomics,” and “precision medicine.” Priority was given to systematic reviews, meta-analyses, clinical studies, and landmark methodological papers.

Artificial Intelligence Technologies in Osteoarthritis

Artificial intelligence (AI) has emerged as a promising tool for addressing several challenges in osteoarthritis (OA), including early diagnosis, disease progression prediction, automated image interpretation, and patient stratification. The rapid growth of AI applications in OA has been driven by the increasing availability of large imaging repositories, electronic health records, and computational resources.[5] Current AI approaches in OA research primarily encompass machine learning (ML), deep learning (DL), and natural language processing(NLP).

Traditional machine learning algorithms have been extensively employed to identify risk factors and predict OA outcomes. Using radiographic and clinical datasets, Zhao et al.[5] demonstrated that machine learning models could identify structural predictors of knee pain severity more effectively than conventional statistical approaches. Their findings suggest that ML can uncover complex relationships between radiographic features and patient-reported outcomes that may not be apparent through traditional analyses. However, the authors also noted that model performance

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depended heavily on dataset quality and feature selection, highlighting an ongoing challenge in translating these models into routine clinical practice.
Deep learning has attracted particular attention because of its ability to automatically learn discriminative features directly from imaging data.

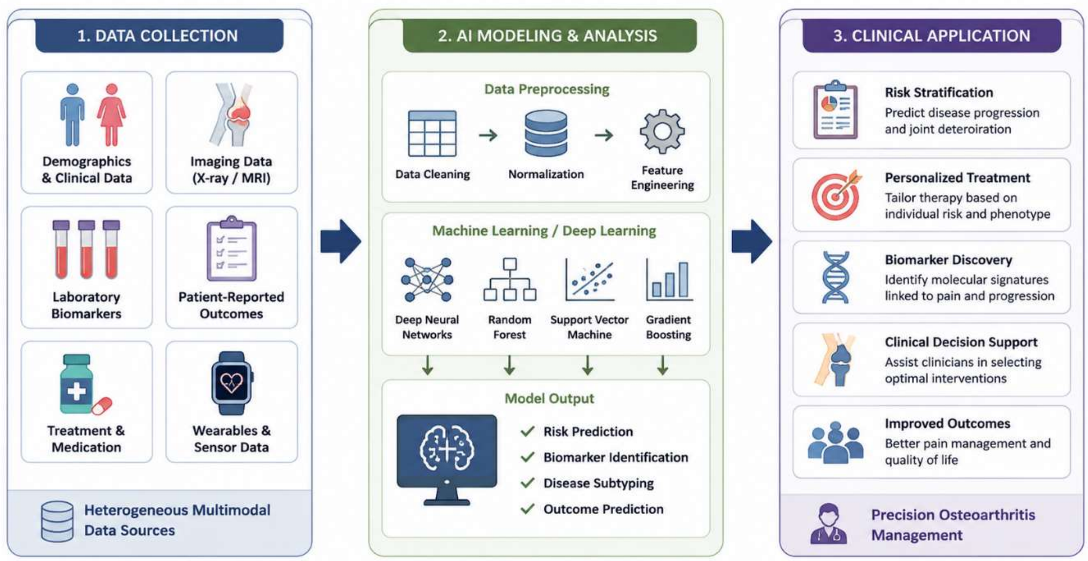

Figure 1: Conceptual framework of artificial intelligence applications in osteoarthritis. Heterogeneous multimodal data sources are processed through machine learning and deep learning algorithms to enable risk prediction, biomarker discovery, disease subtyping, and outcome forecasting, ultimately facilitating personalized treatment planning and precision osteoarthritis management.

Unlike conventional ML methods that rely on manually engineered features, deep learning models can process raw radiographic and magnetic resonance images to identify subtle structural changes associated with OA progression. Subha, Jeyakumar, and Deepa [6] developed a dual convolutional neural network (CNN) architecture optimized using the Gaussian Aquila algorithm and reported high accuracy in detecting and grading knee OA from radiographs. While their results demonstrated the superiority of advanced CNN architectures over traditional classifiers, the study was limited by its reliance on retrospective datasets and the absence of external validation, which may affect generalizability.
Similarly, Fei et al. [7] proposed the use of CNN-derived continuous regression scores rather than conventional Kellgren–Lawrence (KL) grades for OA severity assessment. The authors argued that OA progression occurs along a continuum and is therefore inadequately represented by discrete grading systems. Their approach achieved improved sensitivity in detecting subtle disease progression and highlighted the potential of AI to overcome limitations of traditional radiographic scoring. Nevertheless, implementation of such systems requires extensive validation across diverse patient populations before widespread clinical adoption.
Recent developments have also focused on improving feature extraction and model robustness. Zhang et al. [8] introduced a Dense Multi-Scale convolutional neural network capable of capturing radiographic information at different spatial resolutions. The study reported enhanced diagnostic performance compared with standard CNN architectures, suggesting that multiscale feature learning may improve the detection of early structural abnormalities. However, the authors acknowledged that the "black-box" nature of deep learning remains a significant barrier to clinician acceptance, emphasizing the need for explainable AI frameworks.
Beyond radiography, MRI-based AI models have demonstrated considerable potential in evaluating soft tissue structures that are poorly visualized on plain radiographs. Panwar et al. [9] developed a deep stacking ensemble model that integrated predictions from multiple deep learning architectures to estimate OA severity from MRI images. Their ensemble approach outperformed individual models and demonstrated greater robustness in disease classification. Despite these promising results, MRI-based AI systems may face practical limitations due to higher imaging costs and reduced accessibility compared with conventional radiography.
Natural language processing represents another rapidly expanding area of AI research in OA. By extracting information from unstructured clinical records, NLP

enables large-scale epidemiological studies and automated clinical decision support. Lenskjold et al. [10] demonstrated the feasibility of using AI-assisted methods to construct a large radiographic OA database while substantially reducing manual annotation efforts. Their findings underscore the potential of NLP and automated data extraction techniques to accelerate OA research; however, concerns regarding data standardization, documentation quality, and privacy remain important considerations.

The growing body of evidence supporting AI in OA has been summarized by Mohammadi et al. [11] in a systematic review and meta-analysis. The authors reported consistently high diagnostic accuracy across multiple AI models and imaging modalities, concluding that AI has substantial potential to enhance OA diagnosis and monitoring. Nevertheless, they emphasized that significant heterogeneity existed among studies with respect to datasets, model architectures, validation strategies, and performance metrics. This variability limits direct comparisons between studies and highlights the need for standardized evaluation frameworks.

Collectively, these studies demonstrate that AI technologies have the potential to transform osteoarthritis management by improving diagnostic precision, enabling earlier disease detection, and facilitating personalized treatment strategies. However, despite impressive technical performance, most AI models remain at the proof-of-concept stage. Key challenges include limited external validation, algorithm transparency, dataset bias, and integration into clinical workflows. Future research should therefore focus not only on improving model accuracy but also on enhancing interpretability, reproducibility, and real-world clinical applicability.

AI-Assisted Diagnosis and Imaging Assessment

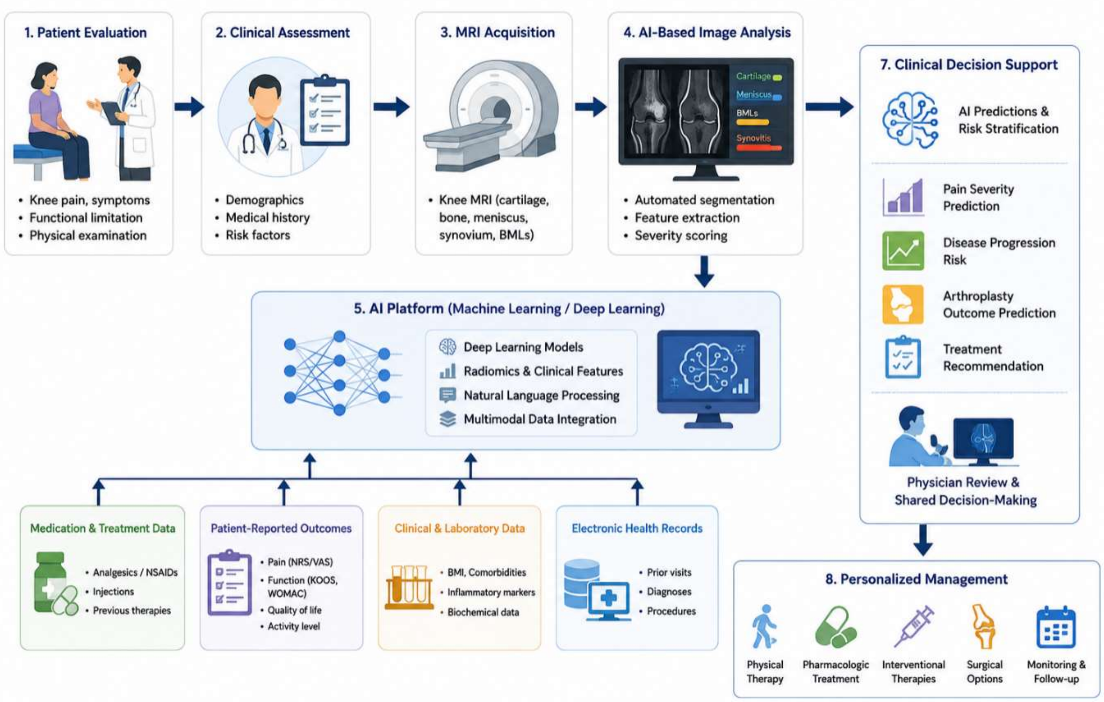

Figure 2: Conceptual framework of AI-assisted personalized osteoarthritis care. Clinical, imaging, laboratory, patient-reported, treatment, and electronic health record data are integrated through machine-learning and deep-learning models to generate risk predictions and treatment recommendations, facilitating precision medicine and shared clinical decision-making.

AI Applications in Imaging Assessment of Osteoarthritis

Radiographic Assessment

Conventional radiography remains the first-line imaging modality for osteoarthritis (OA) diagnosis and epidemiological assessment owing to its accessibility and cost-effectiveness. However, radiographic interpretation is constrained by substantial inter- and intra-observer variability, particularly in the application of the Kellgren–Lawrence (KL) grading system. Consequently, artificial intelligence (AI), particularly deep learning, has emerged as a promising approach to improve the objectivity and reproducibility of radiographic evaluation.

Recent studies have demonstrated that convolutional neural networks (CNNs) can achieve diagnostic performance comparable to expert musculoskeletal radiologists. Subha, Jeyakumar, and Deepa[6] developed a dual CNN framework optimized through a Gaussian Aquila algorithm and reported high accuracy in automated OA detection and grading. Similarly, Fei et al. [7] proposed a regression-based deep learning model that generated continuous OA severity scores rather than conventional categorical KL grades, arguing that OA progression is inherently continuous and inadequately represented by discrete classifications.

The clinical potential of AI-assisted radiography was further highlighted in a large multi-site study by Subramanian et al. [12,13], which analyzed over one million knee radiographs obtained from diverse healthcare settings. Their findings demonstrated robust performance for automated pathology detection and OA grading across different imaging systems and patient populations, suggesting improved generalizability compared with earlier single-center investigations. Nevertheless, despite impressive diagnostic accuracy, most radiographic AI systems remain susceptible to dataset bias and limited external validation, raising concerns regarding their widespread clinical deployment.

MRI-Based Assessment

While radiography primarily evaluates late structural manifestations of OA, magnetic resonance imaging (MRI) enables direct visualization of cartilage, menisci, ligaments, synovium, and subchondral bone, thereby facilitating assessment of early pathological changes. Recent advances in AI-assisted MRI analysis have significantly improved automated segmentation, tissue quantification, and disease prediction.

Panwar et al. [9] demonstrated that deep stacking ensemble models outperform individual neural network architectures in MRI-based OA severity prediction.

Recent work by Wang et al.[14] introduced *CartiSurface*, an anatomically aware deep-learning framework for cartilage thickness mapping from knee MRI. The authors reported improved precision in quantifying cartilage morphology, highlighting the growing role of AI in longitudinal disease monitoring and treatment evaluation. Similarly, Katano et al. [15] demonstrated the feasibility of fully automated AI-based three-dimensional cartilage thickness assessment, further supporting the use of MRI-derived quantitative biomarkers in OA research.

Despite these advances, MRI-based AI systems face several challenges. MRI datasets are generally smaller and more heterogeneous than radiographic datasets, increasing the risk of model overfitting. Furthermore, variability in imaging protocols and scanner specifications may limit model transferability across institutions. These issues underscore the need for standardized multicenter validation studies before routine clinical implementation.

Radiomics

Radiomics has emerged as one of the most promising applications of AI in OA imaging. Unlike conventional image interpretation, radiomics extracts large numbers of quantitative imaging features that characterize tissue texture, intensity, morphology, and spatial relationships. These features may reveal pathological alterations that are not visually detectable by clinicians.

Recent studies have demonstrated that radiomic features extracted from knee imaging can improve automated osteoarthritis classification and grading, providing quantitative biomarkers beyond conventional visual assessment. Furthermore, Fu et al. [16] showed that MRI-derived radiomic signatures from cartilage and subchondral bone could predict both osteoarthritis incidence and progression, while Zhang et al.[17] introduced the LM-CartSeg framework for fully automated cartilage and subchondral bone segmentation, facilitating reproducible radiomics analyses and reducing reliance on manual segmentation. However, radiomics remains challenged by methodological heterogeneity. Differences in image acquisition protocols, feature extraction pipelines, and machine-learning methodologies continue to limit reproducibility across studies. Consequently, although radiomics has demonstrated considerable promise as a source of imaging biomarkers for OA progression and symptom severity, its clinical translation will require greater standardization and external validation.

Emerging Directions and Future Perspectives

Recent literature suggests that OA imaging research is moving beyond isolated imaging algorithms toward integrated, multimodal AI systems. In a comprehensive review, Ou et al. [18] argued that future advances will depend on combining imaging, clinical, genomic, and molecular data within unified AI frameworks capable of supporting precision medicine. Their review highlighted the transition from automated diagnosis toward predictive and personalized disease management.

Similarly, Al Turkestani et al.[19] emphasized the importance of explainable AI by developing interpretable machine-learning models that integrate multiple biomarkers while maintaining clinical transparency. Their work addresses one of the major criticisms of contemporary AI systems—their "black-box" nature—which continues to hinder clinician acceptance.

Overall, contemporary evidence indicates that AI-driven radiography, MRI analysis, and radiomics have substantially enhanced the imaging assessment of osteoarthritis. Nevertheless, despite remarkable technical achievements, challenges related to explainability, reproducibility, external validation, and clinical integration remain significant barriers to widespread adoption. Future research should therefore prioritize multicenter validation, standardized reporting frameworks, and the development of interpretable multimodal models capable of supporting precision osteoarthritis care.

Artificial Intelligence and Pain Prediction in Osteoarthritis

Pain prediction has emerged as one of the most clinically valuable applications of artificial intelligence (AI) in osteoarthritis (OA) research. Unlike structural disease progression, which can be evaluated through imaging, pain is a complex and multifactorial outcome influenced by biomechanical, inflammatory, psychological, and neurophysiological factors.

Consequently, the well-recognized discordance between radiographic severity and symptom burden has challenged traditional OA assessment paradigms. This limitation has stimulated growing interest in AI-based approaches capable of integrating heterogeneous datasets to predict individual pain trajectories and identify patients at risk of symptomatic progression.

Among the earliest studies to demonstrate the utility of AI for pain prediction, Bowes et al. [20] utilized machine-learning techniques to analyze MRI-derived bone shape biomarkers from the Osteoarthritis Initiative (OAI) cohort. The authors reported that subtle alterations in bone morphology were associated with future clinical outcomes, including worsening pain. A major strength of this study was the use of longitudinal imaging data and objectively quantified structural biomarkers rather than conventional radiographic grading. However, despite demonstrating significant associations between bone shape and pain outcomes, the predictive performance remained moderate, suggesting that structural imaging alone cannot fully explain the multidimensional nature of OA pain.

In contrast, Lee et al. [21] adopted a multimodal approach by integrating magnetic resonance imaging with clinical and demographic variables using an ensemble deep-learning framework. Their model predicted eight-year pain trajectories more accurately than models based exclusively on imaging or clinical variables. Compared with the work of Bowes et al., the study by Lee et al. highlighted the added value of combining multiple data sources and demonstrated that pain prediction benefits from incorporating patient-specific characteristics beyond structural pathology. Nevertheless, the model was developed using data from a single cohort (OAI), which may limit its applicability to more diverse populations and healthcare settings.

Further advances were reported by Chen and Or [22] who employed automated machine learning (AutoML) techniques to predict knee pain progression, functional decline, and incident OA. Unlike traditional machine-learning approaches that require extensive manual model optimization, AutoML automatically identifies optimal algorithms and parameter configurations. The principal strength of this study was its scalability and reproducibility, making it potentially attractive for clinical deployment. However, the authors acknowledged that model interpretability remained limited, a common criticism of many AI applications in healthcare. Consequently, although AutoML improved predictive efficiency, it provided relatively limited insight into the underlying biological mechanisms driving pain progression.

Recent perspectives have emphasized that OA pain should be viewed as a whole-joint and whole-person phenomenon rather than merely a consequence of structural degeneration. In a comprehensive review, Khan et al.[23] argued that future pain-prediction models should integrate imaging biomarkers with molecular markers, wearable sensor data, gait analysis, and psychosocial factors. The authors highlighted growing evidence that bone marrow lesions, synovitis, cartilage defects, meniscal abnormalities, and subchondral bone remodeling contribute substantially to pain generation. Their review represents an important conceptual shift from single-modality prediction models toward multimodal precision medicine frameworks. However, many of the technologies discussed remain at an early stage of development, and robust prospective validation studies are still lacking.

A comparison of these studies reveals a clear evolution in AI-based pain prediction. Earlier investigations primarily focused on identifying imaging biomarkers associated with future symptoms, whereas more recent research has increasingly adopted multimodal approaches integrating structural, clinical, and behavioral determinants of pain. While Bowes et al. demonstrated the prognostic value of MRI-derived structural biomarkers, Lee et al. showed that combining imaging and clinical information significantly improves predictive performance. Chen and Or subsequently highlighted the potential of automated machine-learning systems for large-scale risk stratification, whereas Khan et al. proposed a broader precision medicine framework incorporating biological and digital health data.

Despite encouraging progress, several important limitations continue to impede clinical translation. First, most predictive models have been developed and validated using retrospective datasets, particularly the Osteoarthritis Initiative, raising concerns regarding external validity. Second, substantial heterogeneity exists in outcome definitions, imaging protocols, and machine-learning methodologies, making direct comparisons between studies difficult. Third, many deep-learning models function as "black boxes," limiting interpretability and reducing clinician confidence in AI-generated predictions. Finally, psychological determinants of pain, including depression, pain catastrophizing, and central sensitization, remain underrepresented in many predictive models despite their established contribution to symptom severity.

Overall, current evidence suggests that AI-based models outperform conventional radiographic assessment by capturing complex interactions among structural, clinical, and behavioral factors associated with pain. However, no single model has yet achieved sufficient robustness, interpretability, and external validation for routine clinical implementation. Future research should focus on explainable multimodal AI systems, prospective multicenter validation studies, and the integration of imaging, molecular, and patient-reported data to develop clinically applicable tools for personalized pain prediction and management in osteoarthritis.

Artificial Intelligence for Personalized Treatment Selection and Surgical Decision-Making in Oseoarthritis

Personalized Treatment Selection

One of the major challenges in osteoarthritis (OA) management is the substantial heterogeneity in treatment response. Patients with similar clinical and radiographic characteristics often demonstrate markedly different outcomes following conservative, pharmacological, or surgical interventions. This variability has stimulated growing interest in artificial intelligence (AI) as a tool for precision medicine, with the goal of identifying patient-specific predictors of treatment response and optimizing individualized care pathways.

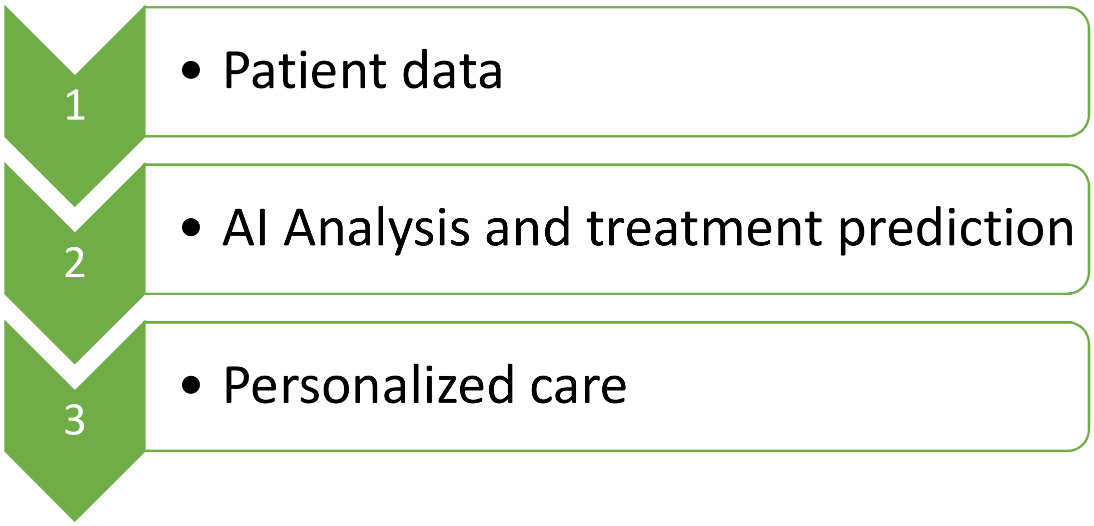

Figure 3: Simplified workflow of AI-assisted personalized treatment selection in osteoarthritis.

Early applications of machine learning in OA primarily focused on disease diagnosis and prognosis; however, recent studies have increasingly explored treatment-response prediction. Using data from the Osteoarthritis Initiative (OAI), Chen and Or [22] demonstrated that automated machine-learning approaches could predict pain progression and functional decline by integrating demographic, clinical, and imaging variables. Although the study was not designed to evaluate specific therapeutic interventions, its findings highlighted the potential of AI-driven risk stratification to identify patients who may benefit from early preventive strategies. A major strength of this approach was its ability to analyze large multidimensional datasets without extensive manual model optimization. However, the limited interpretability of AutoML models remains a significant challenge for clinical adoption.

Recent reviews have suggested that future treatment-selection models should move beyond conventional clinical and radiographic variables. Ou et al.[24] argued that multimodal AI systems integrating imaging biomarkers, genomic data, molecular signatures, and patient-reported outcomes may provide more accurate predictions of treatment response than single-modality approaches. Such models could potentially identify patients most likely to benefit from exercise therapy, rehabilitation programs, intra-articular injections, pharmacological interventions, or emerging disease-modifying OA therapies. The principal strength of this framework lies in its alignment with precision medicine principles; however, the clinical utility of multimodal models remains largely theoretical because prospective validation studies are scarce.

Collectively, these studies indicate that AI may facilitate more individualized treatment planning by identifying patients who are likely to respond to specific interventions while avoiding ineffective therapies. However, despite promising preliminary evidence, most predictive models remain developmental and have not yet demonstrated sufficient external validation for widespread clinical implementation.

AI in Arthroplasty and Surgical Decision-Making

Total knee arthroplasty (TKA) remains the most effective treatment for end-stage OA, yet postoperative outcomes vary considerably among patients. While many individuals experience substantial improvements in pain and function, approximately 15–20% remain dissatisfied following surgery despite technically successful procedures. Consequently, predicting surgical outcomes has become a major focus of AI research.

One of the most influential studies in this area was conducted by Kunze et al.[25], who applied machine-learning algorithms to predict patient-reported outcomes following total joint arthroplasty. Their models successfully identified preoperative factors associated with postoperative satisfaction and functional improvement. A key strength of the study was the incorporation of patient-centered outcome measures rather than solely focusing on surgical complications. However, model performance was influenced by the characteristics of the training cohort, highlighting concerns regarding generalizability.

Subsequent investigations expanded AI applications to perioperative risk assessment. Ramkumar et al.[26] demonstrated that machine-learning models could accurately predict postoperative complications, prolonged hospital stay, and readmission risk following total knee arthroplasty. Compared with traditional regression-based approaches, AI models exhibited superior predictive performance due to their ability to capture nonlinear interactions among clinical variables. Nevertheless, the complexity of these algorithms limited interpretability and may hinder clinician acceptance.

More recently, Karhade et al.[27] reported that machine-learning frameworks could identify high-risk surgical candidates and estimate individualized probabilities of adverse outcomes. Their findings support the integration of AI into shared decision-making processes by providing patients and clinicians with personalized risk estimates. However, the authors emphasized the need for prospective multicenter validation before routine implementation.

Beyond outcome prediction, AI has increasingly been applied to surgical planning and implant selection. Recent studies reviewed by Harkey et al.[28] highlighted the emergence of AI-assisted preoperative planning systems capable of analyzing anatomical and biomechanical characteristics to optimize implant positioning and alignment strategies. Such technologies may improve surgical precision and long-term implant survival. Nevertheless, evidence supporting their superiority over experienced surgeon judgement remains limited, and most systems have yet to undergo rigorous clinical evaluation.

A comparison of current evidence suggests that AI applications in arthroplasty have progressed more rapidly than treatment-selection models for non-surgical interventions. Whereas conservative treatment prediction remains largely investigational, arthroplasty-focused AI systems have demonstrated promising performance in predicting complications, readmissions, patient satisfaction, and functional outcomes. However, both fields face similar challenges, including limited external validation, algorithmic bias, and insufficient transparency. Future research should therefore prioritize explainable AI models, multicenter prospective studies, and integration of patient-reported outcomes to ensure clinically meaningful implementation.

Overall, AI has the potential to transform OA management by supporting precision treatment selection and improving surgical decision-making. While current evidence demonstrates encouraging predictive capabilities, robust validation and clinical integration strategies will be essential before AI can be routinely incorporated into personalized osteoarthritis care.

Emerging Trends

Explainable Artificial Intelligence (XAI)

One of the major criticisms of deep learning systems is their "black-box" nature, which limits clinicians' ability to understand how predictions are generated. Consequently, **Explainable Artificial Intelligence (XAI)** has emerged as a critical area of research aimed at improving transparency, interpretability, and trustworthiness of AI systems. Recent work by **Pahud de Mortanges et al.[29]** highlighted the importance of integrating explainability mechanisms into multimodal and longitudinal medical imaging models, demonstrating how visual explanations, feature attribution methods, and uncertainty estimates can support clinical decision-making. Their review emphasized that explainable models are particularly important in healthcare settings where accountability and patient safety are paramount. Improved interpretability may increase clinician trust, facilitate regulatory approval, and accelerate the integration of AI tools into routine musculoskeletal practice.

Multimodal Learning

Recent advances in AI increasingly focus on **multimodal learning**, which integrates diverse sources of patient information, including medical imaging, clinical variables, laboratory results, genomic data, and wearable-device measurements, into unified predictive frameworks. A comprehensive review by **Krones et al.** [30] demonstrated that multimodal machine learning approaches consistently outperform single-modality models across a variety of healthcare applications by capturing complementary information from heterogeneous data sources. Similarly, **Yildirim et al.**[31] showed that combining vision-language models with clinical data can enhance radiological interpretation and support clinically relevant decision-making workflows. These multimodal approaches are expected to improve diagnostic accuracy, prognostic prediction, and personalized treatment planning in musculoskeletal medicine.

Digital Twins

Digital twin technology represents one of the most promising developments in precision medicine. Digital twins are patient-specific virtual replicas that integrate biological, clinical, imaging, and behavioral data to simulate disease progression and predict treatment outcomes. A landmark scoping review by **Katsoulakis et al.** [32] identified digital twins as a transformative framework for personalized healthcare, enabling real-time monitoring and predictive modeling across multiple medical specialties.

Within musculoskeletal medicine, **Hoyer et al.** [33] established foundational work on a knee-joint digital twin using quantitative MRI biomarkers and machine learning algorithms to predict osteoarthritis progression and the likelihood of knee replacement. Their findings demonstrated the feasibility of creating patient-specific computational models capable of supporting individualized clinical decision-making.

The future of AI in musculoskeletal healthcare is increasingly shaped by advances in explainable AI, multimodal learning, and digital twin technologies. Recent studies by Pahud de Mortanges et al. (2024), Krones et al. (2025), Katsoulakis et al. (2024), Hoyer et al. (2025), and Diniz et al. (2025) demonstrate a clear shift toward transparent, integrated, and patient-specific AI systems. These innovations are expected to improve clinician trust, enhance predictive accuracy, and enable truly personalized musculoskeletal care, positioning AI as a central component of future precision medicine.

Table 1. Current Applications of Artificial Intelligence in Osteoarthritis: Methods and Clinical Benefits

Application	AI Method	Clinical Benefit
Radiographic diagnosis	Deep learning	Automated OA grading
MRI interpretation	CNN models	Early structural detection
Pain prediction	Machine learning	Risk stratification
Rehabilitation planning	Predictive analytics	Personalized therapy
Arthroplasty outcomes	Machine learning	Improved patient selection
Clinical decision support	Multimodal AI	Precision medicine

Interpretation of Table 1

Table 1 summarizes the major contemporary applications of artificial intelligence (AI) in osteoarthritis (OA) management and highlights their associated clinical benefits. Deep learning techniques, particularly in radiographic analysis, have enabled automated OA grading with diagnostic performance approaching that of expert clinicians, thereby improving efficiency and reducing observer variability. Similarly, convolutional neural network (CNN)-based MRI analysis facilitates the early detection of structural joint abnormalities, potentially allowing intervention before substantial disease progression occurs.

Machine-learning algorithms have also been increasingly utilized for predicting pain severity and disease progression, enabling risk stratification and supporting more targeted clinical management. In rehabilitation settings, predictive analytics can assist in developing personalized therapy programs based on individual patient characteristics and expected outcomes. Furthermore, AI models have demonstrated value in predicting arthroplasty outcomes, helping clinicians identify patients most likely to benefit from surgical intervention while optimizing resource allocation.

The emergence of multimodal AI systems represents a significant advancement in clinical decision support. By integrating imaging findings with clinical, laboratory, genetic, and patient-reported data, these systems have the potential to facilitate precision medicine approaches tailored to individual patients. Collectively, these applications illustrate the expanding role of AI across the OA care continuum, from diagnosis and prognosis to treatment planning and outcome prediction. However, despite promising results, further external validation, improved interpretability, and integration into routine clinical workflows remain necessary before widespread clinical implementation can be achieved.

Critical Interpretation of Current Evidence

While AI has demonstrated impressive performance in osteoarthritis research, several important considerations should be acknowledged. Most published models report high diagnostic accuracy under controlled experimental conditions; however, their real-world clinical utility remains uncertain. Many studies rely on retrospective datasets derived from large academic centers, which may not adequately represent the diversity of patients encountered in routine clinical practice. Consequently, algorithm performance may decline when applied to populations with different demographic characteristics, imaging protocols, or disease phenotypes.

Another important issue concerns the distinction between statistical performance and clinical usefulness. A model may achieve excellent classification accuracy yet provide limited benefit if it does not alter clinical decision-making or improve patient outcomes. Future investigations should therefore focus not only on predictive performance but also on clinical impact, cost-effectiveness, and implementation feasibility.

Furthermore, most AI studies have focused primarily on structural imaging abnormalities. Although imaging findings are important, osteoarthritis pain is influenced by multiple biological, psychological, and social factors. Models that rely exclusively on radiographic features may therefore fail to capture the complexity of the patient experience. The integration of psychosocial variables, physical activity measures, and patient-reported outcomes may substantially improve predictive accuracy and clinical relevance.

Comparative Analysis of Current AI Approaches

Different AI approaches offer distinct advantages and limitations in osteoarthritis management.

Deep-learning models applied to radiographic imaging have consistently demonstrated strong diagnostic performance and may eventually support automated screening and reporting. Studies by Antony et al. and subsequent investigations showed that convolutional neural networks can classify radiographic severity with performance approaching expert interpretation. However, radiographic assessment primarily reflects structural disease and may inadequately explain symptom severity. Consequently, radiograph-based models may have limited value for predicting pain outcomes.

In contrast, MRI-based approaches provide more comprehensive assessment of cartilage integrity, bone marrow lesions, synovitis, and meniscal pathology. Studies by Pedoia and colleagues demonstrated that deep-learning analysis of MRI data can identify early structural changes before conventional radiographic abnormalities become apparent. Although MRI-based models may offer superior biological insight, their implementation is constrained by higher costs, longer acquisition times, and reduced accessibility in many healthcare settings.

Machine-learning models integrating clinical and imaging variables appear particularly promising for predicting disease progression. Tiulpin et al. reported

that multimodal models outperform approaches based on imaging alone. This observation suggests that osteoarthritis should be viewed as a multifactorial disease rather than a purely structural disorder. Future predictive systems are therefore likely to derive the greatest benefit from combining imaging findings with demographic, clinical, and molecular information.
Recent multimodal frameworks represent a further evolution of this concept. The 2025 Bone Research review highlighted the growing importance of integrating imaging, electronic health records, genomics, proteomics, and metabolomics into unified predictive models. Such systems may facilitate identification of biologically distinct osteoarthritis endotypes and support precision medicine strategies. Nevertheless, these approaches require extensive computational infrastructure and large, well-annotated datasets, which may limit short-term clinical implementation.

Clinical Relevance for Pain Management

A recurring theme across recent studies is the discrepancy between structural damage and symptom burden. Traditional radiographic grading systems frequently demonstrate only modest correlation with pain severity. This limitation partly explains why some patients experience severe pain despite relatively mild imaging abnormalities.
Artificial intelligence may help bridge this gap by identifying complex patterns associated with pain generation. Emerging evidence suggests that bone marrow lesions, synovitis, periarticular tissue alterations, and biomechanical factors collectively contribute to symptom development. AI algorithms are uniquely suited to analyze these multidimensional relationships and may provide more accurate estimates of future pain trajectories than conventional methods.
However, it is important to recognize that pain is not solely determined by joint pathology. Psychological distress, depression, anxiety, sleep disturbance, and central sensitization substantially influence pain perception. Future AI systems should therefore move beyond structural imaging and incorporate behavioral and psychosocial data to achieve clinically meaningful prediction of patient outcomes.

Author Perspective and Future Outlook

Based on current evidence, the greatest near-term contribution of artificial intelligence is unlikely to be replacement of clinicians. Rather, AI should be viewed as a decision-support technology capable of augmenting clinical judgment. The most successful future systems will likely combine automated image analysis with individualized risk prediction and explainable recommendations that clinicians can interpret and validate.
In the next decade, multimodal and explainable AI models may enable a transition from reactive osteoarthritis management toward proactive and personalized care. Patients at high risk of rapid progression or persistent pain could be identified earlier and offered targeted interventions before substantial joint damage occurs. Such an approach aligns closely with the principles of precision medicine and may ultimately improve outcomes while reducing healthcare costs.

Challenges and Limitations

Despite promising developments, several barriers remain.
First, AI systems require large, diverse, and accurately labeled datasets. Limited dataset diversity may reduce model generalizability.
Second, algorithmic bias remains a concern, particularly when training datasets do not adequately represent demographic diversity.
Third, privacy and cybersecurity issues continue to complicate large-scale healthcare data integration.
Finally, prospective multicenter validation studies remain limited, restricting widespread clinical adoption.

Future Perspectives

Future AI systems are expected to integrate imaging findings, clinical records, laboratory biomarkers, wearable sensor data, and molecular information to provide individualized prediction of pain progression and treatment response.
Advances in explainable AI, federated learning, and multimodal modeling are likely to improve transparency while maintaining patient privacy. Successful implementation will require collaboration among clinicians, engineers, data scientists, regulators, and patients.

Conclusion

Artificial intelligence is rapidly transforming osteoarthritis research and clinical care. Current evidence demonstrates significant potential for improving diagnosis, imaging interpretation, pain prediction, treatment selection, and surgical decision-making. Although important challenges remain, continued technological advances may accelerate the transition toward precision musculoskeletal medicine and individualized pain management.

Table 2. Key Molecular Pathways and Representative Genes Identified in Osteoarthritis Through Artificial Intelligence-Based Genomic Analysis

Molecular Pathway	Representative Genes	Biological Role in OA	Potential Clinical Application

Mitochondrial dysfunction	GRPEL1, MTFP1	Cellular energy regulation	Disease progression monitoring
Inflammatory signalling	IL1B, IL6, CSF1R, TLR7	Synovial inflammation	Pain phenotype characterization
Cellular senescence	MCL1, SIK1, NFKBIA	Age-related joint degeneration	Risk stratification
Hypoxia response	ADM, DDIT3, MAFF	Tissue adaptation to low oxygen	Severity prediction
Autophagy pathways	PDK1, JUN, VEGFA	Chondrocyte survival	Therapeutic target identification
Immune regulation	FCER1G, HLA-DMB, IRAK3	Immune microenvironment modulation	Precision medicine approaches

Data adapted and synthesized from multiple transcriptomic investigations.[34-44]

Interpretative summary of Table 2

Recent AI-assisted transcriptomic studies have consistently identified pathways related to mitochondrial dysfunction, immune activation, cellular senescence, autophagy, and hypoxia as important contributors to osteoarthritis pathogenesis. Machine-learning approaches including LASSO regression, random forests, support vector machine recursive feature elimination, and gradient boosting algorithms have been widely employed to discover candidate molecular signatures. Collectively, these studies suggest that osteoarthritis is a biologically heterogeneous disease and that molecular phenotyping may support future precision medicine strategies.

Declaration of generative AI in scientific writing

While preparing this work, the author(s) used Claude to improve the readability and language of the manuscript. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the manuscript.

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