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# ARTIFICIAL INTELLIGENCE IN ORTHOPAEDIC SURGERY: CLINICAL APPLICATIONS, SOCIOECONOMIC IMPLICATIONS, AND FUTURE DIRECTIONS — A NARRATIVE REVIEW

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## ABSTRACT

**Background:** Artificial intelligence (AI) is transforming orthopaedic medicine, offering new possibilities for improving diagnostic accuracy, optimizing preoperative planning, and enhancing surgical precision. Despite growing evidence of algorithmic performance, clinical translation remains uneven, and a comprehensive synthesis of current evidence is needed to guide orthopaedic practice. This review also evaluates the socioeconomic implications of AI adoption, including clinical trust, accessibility, and the transformation of healthcare delivery models.
**Methods:** This narrative review was conducted in March and April 2026 using PubMed/MEDLINE, Scopus, and Google Scholar. Publications in English from January 2018 to April 2026 were eligible. Methodological quality was assessed using the SANRA scale. A total of 48 sources were included.
**Results:** Deep learning models achieve pooled sensitivity and specificity exceeding 90% in fracture detection on plain radiographs, with regulatory recognition by NICE confirming clinical readiness. AI demonstrates high accuracy in osteoarthritis grading and reduces morphometric measurement times by up to 87%. Deep learning MRI reconstruction reduces acquisition times by up to 90% while maintaining diagnostic quality. AI-driven 3D preoperative templating improves acetabular cup conformity from 72.2% to 90.9% over conventional 2D methods. Robotic-assisted total knee arthroplasty achieves significantly lower mechanical alignment outlier rates than conventional surgery, though short-term patient-reported outcomes remain comparable. Emerging applications include smart sensor-embedded implants, digital twin technology, and large language models supporting clinical documentation.
**Conclusions:** AI demonstrates evidence-supported utility across orthopaedic diagnostics, surgical planning, and arthroplasty. Significant challenges persist regarding external validation, algorithmic transparency, regulatory harmonization, and equitable access. Future research should prioritize prospective multicenter trials, explainable AI frameworks, federated learning, and health economic analyses across diverse healthcare systems.



## KEYWORDS

Artificial Intelligence; Orthopaedic Diagnostics; Surgical Planning; Robotic Surgery; Total Knee Arthroplasty; Socioeconomic Implications

## CITATION

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## 1.Introduction

Musculoskeletal disorders constitute one of the leading causes of global disability and healthcare expenditure, accounting for a substantial proportion of surgical procedures performed worldwide (Gill et al., 2023). Total joint replacements, fracture fixations, and spine surgeries alone represent millions of annual interventions, placing increasing demands on healthcare systems in terms of accuracy, efficiency, and cost containment. In this context, artificial intelligence (AI) has emerged as a transformative force in medicine, with applications spanning diagnostics, treatment planning, intraoperative guidance, and postoperative monitoring.

AI refers broadly to computational systems capable of performing tasks that typically require human intelligence, including pattern recognition, decision-making, and predictive modeling. Within medicine, its most impactful subfield is machine learning (ML), which enables algorithms to identify complex patterns in large datasets without explicit programming. A subset of ML, deep learning (DL), employs hierarchical artificial neural networks and has proven particularly powerful in medical image analysis, achieving performance comparable to clinical experts across multiple diagnostic tasks (Rajpurkar et al., 2022; Song et al., 2025). More recently, large language models (LLMs) and generative AI architectures have begun to extend AI's role from imaging to clinical documentation, patient communication, and decision support (O'Malley et al., 2026). Beyond technical performance, the integration of these models necessitates a critical examination of the evolving human-machine interface and the ethical frameworks governing automated decision-making in healthcare systems.

The orthopaedic surgeon's workflow encompasses three broad phases where AI shows demonstrated promise. In the diagnostic phase, AI-powered image analysis tools can detect fractures, grade osteoarthritis, segment anatomical structures, and identify pathologies in radiographs, CT scans, and MRI studies — often with accuracy rivaling or exceeding that of experienced clinicians (Nowroozi et al., 2024; Elkohail et al., 2025). In the preoperative planning phase, AI systems automate implant templating, predict component sizing, and optimize surgical approaches using patient-specific anatomical data (Han et al., 2025; Altahtamouni et al., 2026). During surgery, robotic platforms integrated with AI algorithms provide real-time guidance, enhance bone resection precision, and support objective alignment verification in arthroplasty procedures (Mostafa et al., 2025). Looking forward, digital twin technology — dynamic, patient-specific virtual replicas integrating imaging, biomechanical, and real-time sensor data — promises to further personalize the entire perioperative pathway (Oettl et al., 2026).

The importance of these developments extends beyond technical performance metrics. Missed fractures represent a leading cause of diagnostic discrepancy in musculoskeletal radiology. AI-assisted detection has been demonstrated to meaningfully reduce diagnostic errors in emergency settings. Lindsey et al. (2018) showed a 47% reduction in wrist fracture misinterpretation rate among emergency medicine clinicians using AI support. In a broader multi-specialty reader study encompassing eight anatomical regions, Guermazi et al. (2022) reported a 29% reduction in missed fractures with AI assistance — a finding reflecting improvement across diverse reader types and skeletal sites rather than a single anatomical location. AI tools functioning as decision-support systems — not as replacements for clinicians — hold the potential to reduce such errors, standardize care quality across institutions, and improve access to expert-level diagnostic capabilities in resource-limited settings (Misir & Yuce, 2025).

Despite growing enthusiasm, clinical translation of AI in orthopaedics remains uneven. While numerous studies demonstrate high model performance in controlled validation settings, real-world implementation is hampered by algorithmic opacity, data bias, regulatory uncertainty, and limited integration with existing clinical information systems (Kiwinda et al., 2025; Andreacchio & Mah, 2025). The heterogeneity of imaging protocols, patient populations, and outcome definitions across studies further complicates direct comparisons.

This narrative review provides a clinically oriented synthesis of AI applications in three core orthopaedic domains: (1) diagnostic imaging encompassing radiography, CT, and MRI; (2) surgical planning and robotic-assisted surgery; and (3) joint arthroplasty, including emerging applications such as digital twins and smart implants. For each domain, we summarize evidence from studies published through April 2026, discuss clinical relevance, and identify key limitations and future research directions.

## 2. Methodology

This study was designed as a narrative review aimed at synthesizing current evidence on the applications of artificial intelligence in orthopaedic diagnostics, surgical planning, and joint arthroplasty, with additional consideration of socioeconomic implications. A narrative approach was selected due to the heterogeneity of study designs, methodologies, and outcome measures across the available literature, which precluded formal meta-analysis.

### 2.1. Literature Search Strategy

A structured literature search was conducted between March 1 and April 15, 2026, using the following electronic databases: PubMed/MEDLINE, Scopus, and Google Scholar. The search strategy combined controlled vocabulary (e.g., MeSH terms) and free-text keywords. Core search terms included: “artificial intelligence”, “machine learning”, “deep learning”, “convolutional neural network”, “orthopaedic surgery”, “musculoskeletal imaging”, “fracture detection”, “osteoarthritis”, “surgical planning”, “robotic surgery”, “total knee arthroplasty”, “total hip arthroplasty”, “digital twin”, “smart implant”, and “implant templating”.

These terms were combined using Boolean operators (AND, OR) to maximize sensitivity and specificity. An example search string used in PubMed was: (“artificial intelligence” OR “machine learning” OR “deep learning”) AND (“orthopaedic surgery” OR “musculoskeletal imaging” OR “arthroplasty”) AND (“fracture detection” OR “osteoarthritis” OR “robotic surgery” OR “surgical planning”). The search was limited to articles published in English between January 2018 and April 2026. Additional hand-searching of reference lists from key articles was performed to identify relevant studies not captured in the initial database search.

### 2.2. Study Selection

The initial database search yielded 312 records. After removal of duplicates, 247 articles remained for title and abstract screening. Of these, 96 articles were selected for full-text review based on relevance to the study objectives. Following full-text assessment, 48 articles were included in the final synthesis.

**Studies were included if they:**

- addressed applications of artificial intelligence in orthopaedic diagnostics, imaging, surgical planning, or arthroplasty,
- reported clinically relevant outcomes or quantitative performance metrics (e.g., sensitivity, specificity, accuracy, AUROC),
- were original research articles, systematic reviews, or meta-analyses.

**Studies were excluded if they:**

- focused exclusively on non-orthopaedic musculoskeletal conditions without surgical relevance,
- described purely theoretical or experimental AI models without clinical application,
- lacked peer review or sufficient methodological transparency.

### 2.3. Data Extraction and Synthesis

Data were extracted qualitatively from included studies, focusing on study design, sample size, AI methodology, clinical application, and reported performance outcomes. Given the heterogeneity of included studies, a thematic synthesis approach was adopted. Evidence was grouped into three primary domains: (1) diagnostic imaging, (2) surgical planning and robotic-assisted surgery, and (3) joint arthroplasty.

Within each domain, findings were synthesized narratively with emphasis on clinical relevance, reproducibility, and translational potential. Particular attention was given to studies with external validation, large datasets, or prospective design.

### 2.4. Quality Assessment

The methodological quality of the narrative review was guided by the SANRA (Scale for the Assessment of Narrative Review Articles) framework (Baethge et al., 2019), a validated tool developed to assess the quality and transparency of non-systematic reviews. The SANRA scale evaluates six key domains, including the justification of the review's importance, clarity of aims, description of the literature search, appropriate referencing, scientific reasoning, and presentation of relevant data. In the present study, SANRA principles were applied to ensure transparency in literature selection, balanced interpretation of evidence, and coherent synthesis of findings. While a formal numerical SANRA score was not calculated, the framework informed the overall methodological approach and reporting structure of the review.

### 2.5. Limitations of the Methodology

Several limitations inherent to the narrative review design must be acknowledged. First, the lack of a formal systematic review protocol introduces potential selection bias. Second, the exclusion of non-English publications may limit the generalizability of findings. Third, the rapidly evolving nature of artificial intelligence research means that recently published or preprint studies may not be fully represented. Finally, heterogeneity across study designs and outcome measures limits direct comparability between studies. Despite these limitations, this approach enables a comprehensive and clinically contextual synthesis of a rapidly evolving field, aligning with the exploratory and interdisciplinary scope of the present review.

## 3. Results

A structured overview of key applications of artificial intelligence in orthopaedics, including their clinical utility and underlying methodologies, is presented in Table 1.

**Table 1.** Key applications of artificial intelligence in orthopaedics

| Domain | Application | AI Techniques | Clinical Benefit | Key References |
|---|---|---|---|---|
| Diagnostic imaging (X-ray) | Fracture detection | CNN, ResNet, VGG | Increased sensitivity and reduced misdiagnosis rates | Nowroozi et al., 2024; Lindsey et al., 2018 |
| Diagnostic imaging (X-ray) | Osteoarthritis grading | CNN, DL classification models | Improved diagnostic accuracy and inter-rater reliability | Zhao et al., 2025; Guo et al., 2025 |
| Diagnostic imaging (X-ray/CT) | Automated morphometric measurements | DL segmentation models | Reduced measurement time, high reproducibility | Oettl et al., 2025 |
| CT imaging | Bone segmentation and fracture classification | U-Net, GANs | High-precision anatomical segmentation enabling patient-specific surgical planning | Han et al., 2025 |
| MRI imaging | Soft tissue injury detection | DL models, multimodal AI | Accurate detection of ligament, cartilage, and meniscal injuries | Siouras et al., 2022; Luo et al., 2026 |
| Preoperative planning | Implant sizing and positioning | 3D AI modeling, ML prediction | Improved implant fit and surgical precision | Altahtamouni et al., 2026; Han et al., 2025 |
| Robotic surgery | Bone resection and alignment | AI-integrated robotic systems | Reduced mechanical alignment outliers (RR = 0.33); bone resection accuracy within ±0.5 mm; potential to narrow outcome disparities across institution types | Mostafa et al., 2025; Ng et al., 2025 |
| Arthroplasty (TKA/THA) | Outcome prediction and risk stratification | ML predictive models | Personalized risk stratification, preoperative counseling, and hospital resource planning; variable performance across outcome domains | Kim et al., 2025; Song et al., 2025 |
| Postoperative care | Prosthetic loosening detection and implant identification from radiographs | DL, sensor-based AI | Detection of prosthetic loosening with radiologist-level accuracy; identification of implant manufacturer and model from radiographs with up to 99% accuracy — clinically relevant for revision surgery planning | Kim et al., 2023; Karnuta et al., 2021 |
| Emerging technologies | Digital twins, smart implants | Multimodal AI, sensor integration | Potential for continuous in vivo monitoring and predictive implant performance modeling | Kumar et al., 2025; Oettl et al., 2026 |

*Note.* AI = artificial intelligence; CT = computed tomography; MRI = magnetic resonance imaging; THA = total hip arthroplasty; TKA = total knee arthroplasty; CNN = convolutional neural network; DL = deep learning; ML = machine learning; GAN = generative adversarial network; RR = risk ratio.

### 3.1. AI in Orthopaedic Imaging: Radiography, CT, and MRI

Medical imaging is the foundation of orthopaedic diagnosis and treatment planning. AI applications in this domain span multiple modalities and clinical tasks, with the volume of published evidence growing exponentially and the first commercially deployed, regulatory-approved systems now entering routine clinical practice.

#### 3.1.1. AI in Plain Radiography (X-ray)

Conventional radiography remains the most widely used first-line imaging modality in orthopaedics due to its accessibility, speed, and low cost. It is also the modality for which AI diagnostic support is most extensively studied and — in several jurisdictions — already deployed in routine clinical practice.

Fracture detection has received the most research attention in orthopaedic AI imaging. Pooled sensitivity and specificity exceeding 90% have been reported for deep learning models detecting fractures on plain radiographs across multiple anatomical sites, though significant heterogeneity exists across studies (Nowroozi et al., 2024). Models including CNNs, ResNet, and VGG16 demonstrate superior diagnostic performance compared to traditional methods across diverse imaging modalities and skeletal regions (Kutbi, 2024). These findings are corroborated by a meta-analysis of CE-marked and FDA-cleared commercial fracture detection systems, which demonstrated consistently high diagnostic accuracy across validated clinical products (Husarek et al., 2024). Reported sensitivities and specificities for deep learning fracture detection across multiple external validations typically range from 85% to 95%, with AI additionally supporting workflow triage and clinician diagnostic confidence (Elkohail et al., 2025). Foundational evidence supporting this clinical utility was provided by Lindsey et al. (2018), who trained a deep learning model on annotations from 18 subspecialized orthopaedic surgeons to approximate expert-level diagnostic performance. When used by emergency medicine clinicians, the model improved wrist fracture detection, increasing sensitivity from 80.8% to 91.5% and reducing the misinterpretation rate by 47.0% (95% CI, 37.4–53.9%) compared with unaided reading.

A significant regulatory milestone was reached in 2024, when the UK's National Institute for Health and Care Excellence formally recommended specific AI-based tools for fracture detection in clinical practice, marking a transition of AI-assisted orthopaedic imaging from experimental research to recognized standard of care (Oettl et al., 2025). Fracture detection shows the highest level of maturity and clinical readiness among AI orthopaedic imaging applications, with confirmed potential to enhance diagnostic performance across multiple modalities (Longo et al., 2025a).

Osteoarthritis classification on plain radiographs and MRI represents another established AI application in orthopaedic imaging. AI models have shown high accuracy in distinguishing osteoarthritis (OA) grades with particular strength in early-stage detection, while AI-aided radiographic analysis has been shown to improve inter-rater reliability among clinicians (Oettl et al., 2025). Deep learning models grading knee OA severity according to the Kellgren–Lawrence scale have demonstrated clinically relevant diagnostic performance across multiple external validation datasets, with multi-classification approaches proving particularly suitable for clinical OA assessment (Zhao et al., 2025). Excellent diagnostic performance for OA grading has been further confirmed across multiple studies, with CNNs being the most widely used architecture across classification, segmentation, and risk prediction tasks (Guo et al., 2025).

Automated morphometric measurement — including hip-knee-ankle angle, Cobb angle in scoliosis, and knee alignment parameters — represents an additional domain of clinical relevance. AI has demonstrated measurement precision equivalent to expert-level assessment, with intraclass correlation coefficients exceeding 0.97 for major scoliotic curves and 0.979 for whole-leg length measurements, while reducing measurement times by up to 87% in high-volume settings (Oettl et al., 2025). In 2024–2025, explainable AI (XAI) techniques incorporating uncertainty quantification have been increasingly integrated into imaging tools, addressing the previously critical "black box" limitation and improving clinician trust in model outputs (Oettl et al., 2024).

Beyond plain radiography, CT imaging extends AI capabilities into three-dimensional anatomical analysis, enabling applications that are not feasible with conventional radiographs.

#### 3.1.2. AI in Computed Tomography (CT)

Computed tomography provides three-dimensional anatomical information indispensable for complex fracture characterization, surgical planning, and implant templating. AI applications in CT have focused on automated bone segmentation, fracture classification, bone metastasis detection, and generation of patient-specific surgical models.

Automated bone segmentation using CT data constitutes a fundamental step in downstream AI applications. Deep learning models — particularly U-Net architectures, Double U-Net variants, and GAN-based frameworks — have achieved Dice similarity coefficients above 0.90 for pelvis, femur, tibia, and vertebral column structures (Han et al., 2025). GAN models additionally enable cross-modal image synthesis and data augmentation, addressing the critical problem of limited annotated medical datasets — a persistent bottleneck in orthopaedic AI development.

For fracture detection, AI has demonstrated particular utility in high-complexity, multi-fragment fractures that may be overlooked on plain radiographs. Inoue et al. (2022) demonstrated that an object detection algorithm applied to whole-body trauma CT achieved automated fracture screening with high sensitivity, with subsequent studies confirming applicability across vertebral, pelvic, and long-bone fractures. Pooled AUROCs typically ranging from 0.85 to 0.97 have been reported for CT-based fracture detection across imaging modalities in a systematic review and meta-analysis synthesizing studies through 2024 (Jung et al., 2024).

Bone metastasis detection represents an area of growing clinical importance. AI models applied to CT have demonstrated AUROCs of 0.95–0.98 for detecting bone metastases from breast, prostate, and lung primary cancers, with performance comparable to individual physician assessments (Song et al., 2025). Across 34 studies, AI applied to CT demonstrated accuracy ranging from 0.44 to 0.99 in distinguishing benign from malignant bone lesions, with sensitivity from 0.63 to 1.00 and specificity from 0.73 to 0.96 — a range reflecting maturity variation across anatomical sites and model architectures (Kumar et al., 2025).

While CT excels in bone characterization, MRI remains the modality of choice for soft tissue assessment, and AI integration in this domain presents distinct technical challenges and clinical opportunities.

#### 3.1.3. AI in Magnetic Resonance Imaging (MRI)

MRI is the gold standard for evaluating soft tissue structures including articular cartilage, menisci, ligaments, and intervertebral discs, as well as early bone marrow pathology. The high dimensionality and acquisition complexity of MRI present both opportunities and challenges for AI integration.

In knee MRI, systematic reviews confirm that deep learning models accurately detect ACL tears, meniscal tears, cartilage lesions, and bone contusions, with sensitivity and specificity frequently exceeding 85% (Siouras et al., 2022). Multimodal models combining standard morphological MRI with quantitative compositional sequences (T2 mapping, T1rho) show promise for early OA detection prior to visible structural damage — a capability enabling earlier therapeutic intervention. Combining complementary information from multiple modalities overcomes the inherent limitations of single-modality approaches, enabling more comprehensive structural, functional, and metabolic assessments (Luo et al., 2026).

Deep learning-based MRI reconstruction algorithms can reduce scan times by up to 90% while maintaining diagnostic quality, with studies demonstrating 60% acceleration in volumetric brain MRI and 40% faster spinal MRI scans matching or exceeding standard care quality (Oettl et al., 2025). This has direct implications for healthcare efficiency and the feasibility of MRI-based population screening. In 2025, these techniques received increasing regulatory attention, with the FDA clearing several AI-based MRI reconstruction tools for clinical use.

Spine MRI analysis has become a high-priority application area given the high prevalence of degenerative disc disease and the clinical complexity of radiological reporting. AI models for automated grading of disc degeneration, detection of spinal canal stenosis, and vertebral fracture classification have achieved performance approaching specialist radiologist accuracy. Natural language processing applied to radiology report text represents a complementary approach, enabling structured data extraction from unstructured clinical notes and supporting large-scale epidemiological research (Misir & Yuce, 2025).

### 3.2. AI in Surgical Planning and Robotic-Assisted Surgery

The application of AI to surgical planning represents a logical extension of its diagnostic imaging capabilities, enabling the transition from data interpretation to actionable clinical decision support. In orthopaedics, preoperative planning encompasses implant selection and sizing, surgical approach determination, osteotomy planning, and patient-specific risk stratification. Robotic systems — representing the operational endpoint of AI-assisted planning — have achieved widespread clinical adoption, particularly in joint arthroplasty.

#### 3.2.1. AI-Assisted Preoperative Planning

Traditional preoperative planning for joint replacement surgery involves manual or semi-automated templating on digital radiographs — a process subject to measurement error and inter-observer variability. AI-based planning systems leverage segmented CT or MRI data to generate three-dimensional patient-specific anatomical models, from which optimal implant size, position, and alignment can be computationally derived.

Superiority of AI-driven 3D planning over conventional 2D templating has been demonstrated across multiple outcomes. In a systematic review of 47 studies, Eskandar (2025) reported that AI-driven 3D modeling improved acetabular cup conformity from 72.2% to 90.9% and femoral stem accuracy from 66.7% to 87.3% over conventional 2D templating. Surgical risk prediction models achieved AUROCs exceeding 0.85 for postoperative complications. These findings are consistent with a retrospective controlled study by Hu, Y., et al. (2026), which showed that AI-robotic-assisted TKA improved femoral prosthesis prediction accuracy from 52.3% to 79.5% and tibial accuracy from 61.4% to 84.1% versus conventional manual planning.

An AI-powered preoperative planning system for THA (AIHIP), developed using over 1.2 million CT images from 3,000 patients and validated prospectively in 120 patients, demonstrated superior accuracy, imaging outcomes, and clinical performance compared to traditional planning methods, significantly reducing planning time and manpower requirements (Han et al., 2025). These findings are further supported by a systematic review and meta-analysis by Altahtamouni et al. (2026), specifically comparing AI-assisted 3D preoperative planning to traditional 2D templating in THA, which concluded that 3D AI systems consistently outperform 2D methods in implant size prediction and positioning accuracy.

Computational prediction of intraoperative bone resection parameters represents a frontier application in AI-assisted planning. Hu, M., et al. (2026) evaluated an AI decision support system predicting 17 intraoperative parameters for robotic-assisted TKA in 54 knees, achieving high precision within 0–1 mm/° tolerance across all dimensions. Such systems, if validated at scale, could transform the relationship between preoperative planning and intraoperative execution, reducing surgeon cognitive load and increasing procedural consistency.

The transition from preoperative planning to intraoperative execution is increasingly mediated by robotic surgical platforms, which represent the most mature form of AI-assisted intervention in orthopaedic surgery.

#### 3.2.2. Robotic-Assisted Surgery

Robotic surgical systems integrate preoperative imaging data, real-time anatomical tracking, and computer-controlled bone preparation tools to enhance surgical precision beyond what is achievable manually. Robotic TKA currently accounts for approximately 13% of all knee replacements performed in the United States (Inabathula et al., 2024), and according to projections cited in the 2023 AJRR Annual Report, this proportion could reach up to 50% by 2030, though this figure reflects an optimistic growth scenario (American Joint Replacement Registry, 2023).

Currently available robotic platforms for knee and hip arthroplasty include Mako (Stryker), ROSA Knee (Zimmer Biomet), CORI and Navio (Smith & Nephew), and TSolution One (Think Surgical). Fan et al. (2025) classified these systems as semi-active — employing haptic guidance to constrain the surgeon within a predefined safe zone — or fully active, performing autonomous bone milling with minimal manual input, with each category presenting distinct accuracy and flexibility trade-offs.

Building upon this taxonomy, Walgrave and Oussedik (2023) highlighted the critical operational distinction between image-dependent systems, which rely on preoperative CT for high-precision planning, and imageless systems utilizing intraoperative landmark registration. While image-based platforms such as Mako offer superior bone resection accuracy, imageless systems such as Navio and CORI provide a more streamlined clinical workflow by eliminating radiation exposure and reducing preoperative logistical constraints (Walgrave & Oussedik, 2023).

The precision advantage of robotic assistance in bone preparation has been confirmed by meta-analytic evidence. Mostafa et al. (2025), analysing 21 randomized controlled trials, confirmed that robotic-assisted TKA achieves significantly lower mechanical alignment outlier rates (RR = 0.33) and more precise deviation from the target mechanical axis compared to conventional manual TKA. Concerning functional outcomes, the review found no statistically significant differences in patient-reported outcome measures including WOMAC and OKS at short to medium-term follow-up — suggesting that precision improvements may require longer follow-up periods and patient-specific alignment strategies to fully translate into measurable clinical benefit.

Beyond alignment accuracy, AI algorithms embedded in robotic platforms are increasingly capable of optimizing surgical strategy in real time rather than merely executing a predetermined plan. Ng et al. (2025) demonstrated that an AI-driven algorithm for intraoperative 3D implant positioning achieved surgeon-defined target gaps and alignment with ±0.5 mm accuracy while significantly reducing soft tissue balancing time — a capability with particular relevance for reducing intraoperative decision-making burden across surgeons of varying experience levels. The integration of AI with robotic surgical systems carries broader implications for equity in orthopaedic care. By standardizing bone preparation precision and reducing dependence on individual surgeon experience, these technologies hold potential to narrow outcome disparities between high- and low-volume institutions (O'Malley et al., 2026).

The learning curve associated with robotic systems remains an important implementation consideration. Available evidence suggests operative times for robotic TKA converge with manual techniques after approximately 30–40 procedures, though reported learning curves range from 25 to 70 cases depending on the system and individual surgeon competencies (Ejnisman et al., 2024). Beyond operative time, economic barriers remain substantial. Robotic TKA has been reported to cost an average of $2,400 more per case than conventional surgery, based on a large-scale analysis of the National Inpatient Sample encompassing over 558,000 procedures, with device acquisition costs adding several million dollars depending on the vendor (Aggarwal et al., 2024). Together, these factors represent significant barriers to universal adoption, particularly in lower-resource healthcare settings.

### 3.3. AI in Joint Arthroplasty: TKA and THA

Total knee and hip arthroplasty are among the most commonly performed elective surgical procedures worldwide. Outcomes are highly sensitive to component positioning, sizing, and alignment — parameters that AI and robotic systems are specifically designed to optimize. Beyond surgical precision, AI is increasingly applied across the entire perioperative arthroplasty pathway, from patient selection and risk stratification to postoperative rehabilitation monitoring.

#### 3.3.1. AI in Total Knee Arthroplasty (TKA)

AI has demonstrated utility across all stages of the TKA pathway. Machine learning models trained on clinical registry data demonstrate strong performance in predicting postoperative complications, length of hospital stay, implant survivorship, and patient-reported satisfaction, enabling more personalized preoperative counseling and resource allocation (Song et al., 2025; Misir & Yuce, 2025). In patient selection, ML algorithms can predict postoperative complications such as transfusion needs with reported AUROCs up to 0.842. Deep learning techniques additionally facilitate 3D anatomical reconstruction and implant size prediction, with some models achieving over 90% accuracy for exact component sizing (Kim et al., 2025). Robotic-assisted surgeries incorporating AI-guided planning consistently improve implant alignment and procedural consistency, though long-term functional outcomes remain inconclusive — highlighting the need for prospective registries with multi-year follow-up (Eskandar, 2025).

AI-generated patient-specific instrumentation (PSI) uses CT or MRI segmentation to produce custom cutting blocks tailored to individual anatomy. Newer PSI iterations incorporate AI-driven planning, with studies consistently showing superiority over conventional 2D templating in implant size prediction and alignment — particularly in complex deformity cases (Sappey-Marinier et al., 2025). The question of optimal alignment philosophy — mechanical versus kinematic versus functional alignment — has gained renewed relevance in the context of robotic TKA, which enables consistent execution of diverse targets. AI models capable of personalizing alignment goals based on individual biomechanics and patient-reported preferences represent an emerging frontier in outcome optimization (Walgrave & Oussedik, 2023).

Postoperative AI applications represent an equally important dimension of TKA care. ML models applied to serial radiographs can identify prosthetic loosening with accuracy comparable to experienced radiologists (Kim et al., 2023). Deep learning algorithms have additionally proved capable of identifying arthroplasty implant manufacturers and models from plain radiographs with 99% accuracy — solving a clinically relevant problem in revision surgery, where approximately 10% of components remain unidentified preoperatively, increasing operative time and costs (Karnuta et al., 2021).

While TKA presents primarily biomechanical challenges related to alignment and soft tissue balancing, THA introduces distinct anatomical complexity requiring precise three-dimensional acetabular and femoral reconstruction.

#### 3.3.2. AI in Total Hip Arthroplasty (THA)

THA presents distinct anatomical challenges regarding acetabular cup positioning, femoral stem sizing, and leg length restoration. Deep learning models have transformed OA severity grading and implant identification by automating traditionally manual processes with high accuracy, while AI-powered preoperative planning systems optimize hip joint center prediction and complication identification using multimodal data. Robotic-assisted THA further enhances precision with real-time feedback, reducing dislocation and leg length discrepancy complications (Andriollo et al., 2025).

The strongest meta-analytic evidence for AI-assisted 3D THA planning was provided by Altahtamouni et al. (2026), who confirmed consistent superiority of 3D AI systems over conventional 2D templating in implant size prediction and positioning accuracy. This is of particular relevance for complex primary cases involving acetabular dysplasia, prior osteotomies, or significant bone loss. Complementary evidence from a broad review by Longo et al. (2025b) suggests that AI and ML models may further help predict postoperative outcomes, enhance clinical decision-making, and streamline perioperative care by reducing time, costs, and overall complexity.

Emerging 2025–2026 applications extend AI's role in arthroplasty beyond the operative episode toward continuous postoperative surveillance. AI-powered smart implants embedded with sensors enable in vivo monitoring of forces, micromotion, and early loosening signals, with energy harvesting via piezoelectric materials allowing sensor operation without battery dependency (Kumar et al., 2025). Digital twin technology — creating dynamic, patient-specific virtual replicas integrating imaging, biomechanical simulation, and real-time implant sensor data — represents the conceptual next step, enabling continuous monitoring and predictive modeling of implant performance throughout the implant lifecycle (Oettl et al., 2026). These emerging technologies, while not yet widely deployed in clinical practice, signal a broader trajectory toward fully integrated, AI-driven perioperative orthopaedic care — a theme explored further in the Discussion.

## 4. Discussion

The evidence synthesized in this review demonstrates that AI has achieved meaningful clinical impact across multiple orthopaedic domains, with the most consistent evidence for fracture detection, OA grading, and surgical alignment precision. However, translation of algorithmic performance into demonstrated patient benefit remains incomplete, and significant barriers to widespread adoption persist. The performance characteristics and limitations of current AI applications are summarized in Table 2 and form the basis for the following discussion.

**Table 2.** Performance metrics, strengths, and limitations of current AI applications in orthopaedic practice

| Application | Reported Performance | Strengths | Limitations | Key References |
|---|---|---|---|---|
| Fracture detection (X-ray) | Sensitivity/specificity: ~85–95% | High diagnostic accuracy, supports workflow triage | Dataset bias, variability across anatomical sites | Nowroozi et al., 2024; Husarek et al., 2024 |
| Osteoarthritis grading (X-ray) | High multi-class classification accuracy; AUC >0.90 in external validation | Improved consistency, early-stage detection | Limited generalizability across populations | Zhao et al., 2025; Guo et al., 2025 |
| CT-based fracture detection | AUROC: ~0.85–0.97 | Effective in complex multi-fragment fractures | Performance variability across anatomical sites and model architectures | Jung et al., 2024; Kumar et al., 2025 |
| MRI soft tissue analysis | Sensitivity/specificity often >85% | Comprehensive structural and functional assessment | Data heterogeneity, high acquisition complexity, limited standardization | Siouras et al., 2022; Luo et al., 2026 |
| Preoperative planning (THA/TKA) | Implant size prediction accuracy up to ~90% | Improved implant fit and surgical precision | Dependence on imaging quality and protocol standardization | Altahtamouni et al., 2026; Eskandar, 2025 |
| Robotic-assisted surgery | Reduced alignment outliers (RR = 0.33) | High bone resection precision and reproducibility | High cost, learning curve; no demonstrated superiority in short-term patient-reported outcomes | Mostafa et al., 2025; Ejnisman et al., 2024 |
| Outcome prediction models | AUROC up to 0.842 (transfusion risk prediction); variable across outcome domains | Personalized risk stratification and preoperative counseling | Limited external validation, single-institution datasets | Kim et al., 2025; Misir & Yuce, 2025 |
| Implant identification (TKA) | Accuracy up to 99% | Clinically valuable in revision surgery planning | Limited dataset diversity; validated primarily for knee implants | Karnuta et al., 2021 |
| Smart implants / digital twins | Emerging — limited clinical validation | Potential for continuous in vivo monitoring and predictive implant performance modeling | Regulatory uncertainty, ethical and cybersecurity concerns, high implementation costs | Kumar et al., 2025; Oettl et al., 2026 |

*Note.* AI = artificial intelligence; CT = computed tomography; MRI = magnetic resonance imaging; THA = total hip arthroplasty; TKA = total knee arthroplasty; AUROC = area under the receiver operating characteristic curve; RR = risk ratio.

### 4.1. Consistency of Evidence and Clinical Significance

The regulatory recognition of AI fracture detection tools by NICE (2024) and the FDA signals a transition from experimental to accepted clinical utility in diagnostic imaging. Robotic-assisted arthroplasty has a substantial evidence base confirming mechanical alignment advantages, though functional outcome superiority over longer follow-up periods remains to be definitively established. The most compelling evidence increasingly emphasizes AI's role as a collaborative decision-support tool — augmenting clinician performance rather than replacing clinical judgment. Studies demonstrating that AI increases clinician accuracy and inter-observer agreement more directly support clinical adoption than standalone model performance benchmarks (Oettl et al., 2025; O'Malley et al., 2026).

Beyond imaging and surgical precision, a particularly significant development in 2025–2026 has been the emergence of large language models (LLMs) in orthopaedic clinical workflows. LLMs have established utility in clinical documentation, coding support, surgical education, research literature synthesis, and patient communication (O'Malley et al., 2026). Unlike image-based AI tools, however, LLMs introduce distinct risks in clinical contexts — including hallucination of clinical facts, inconsistent output reliability, and the absence of standardized validation frameworks for medical use. These limitations underscore that while LLMs may reduce administrative burden and free clinician time for direct patient care, their integration into clinical decision-making requires separate and careful regulatory oversight.

### 4.2. Limitations and Challenges

Several methodological and systemic challenges temper enthusiasm for AI in orthopaedics. First, the majority of published AI models have been developed and validated on retrospective single-institution datasets, which may not reflect the diversity of imaging protocols, patient demographics, and clinical settings encountered in real-world practice. External validation across independent, geographically diverse cohorts remains the exception rather than the rule (Elkohail et al., 2025; Andreacchio & Mah, 2025). These observations are consistent with a contemporaneous narrative review by Glinkowski et al. (2026), who identified limited external validation, algorithmic opacity, and regulatory fragmentation as principal barriers to the clinical deployment of AI across multiple orthopaedic domains.

Second, most existing AI models function as "black boxes," providing diagnostic outputs without interpretable explanations. The emerging field of explainable AI (XAI) seeks to address this by providing saliency maps and feature attribution methods that allow clinicians to understand which imaging features drove a prediction (Oettl et al., 2024). Closely related is uncertainty quantification — enabling models to communicate confidence levels alongside predictions — which has been identified as a development priority for high-stakes orthopaedic applications (Eskandar, 2025).

Third, data fragmentation and the absence of standardized imaging protocols create practical barriers to AI development and deployment. Federated learning — enabling distributed model training across institutions without centralizing patient data — represents a promising solution to this challenge while preserving privacy, and has been specifically proposed as a priority for spine surgery AI research (Shahzad et al., 2024).

Fourth, equity concerns remain acute. AI models trained predominantly on high-income, white-majority populations may perform less accurately in underrepresented demographic groups, potentially exacerbating existing healthcare disparities (Siddiqui et al., 2024). These limitations are not unique to orthopaedics. Rajpurkar et al. (2022) identified dataset limitations, single-source bias, and absent prospective validation as systemic barriers to clinical AI deployment across medical specialties — confirming that orthopaedic AI faces challenges common to the broader field.

### 4.3. Regulatory and Ethical Considerations

The regulatory landscape for medical AI devices continues to evolve rapidly and unevenly across jurisdictions. In the US, the FDA has approved several AI-based orthopaedic imaging tools as Software as a Medical Device (SaMD), typically under the 510(k) pathway. The EU Medical Device Regulation (MDR) imposes more stringent post-market surveillance requirements. Ensuring regulatory frameworks keep pace with continuously learning algorithms — which may change performance after deployment — remains an unresolved governance challenge globally. These challenges are compounded by the problem of continual learning: models that update their parameters following deployment may alter their performance characteristics in ways that existing approval frameworks, designed for static locked algorithms, are ill-equipped to evaluate (Rajpurkar et al., 2022).

A related and underexplored dimension concerns legal accountability when AI-assisted decisions result in adverse outcomes. As AI tools become integrated into diagnostic and surgical workflows, the distribution of responsibility among developers, institutions, and individual clinicians remains legally and ethically ambiguous. Kiwinda et al. (2025) argue that clear accountability frameworks are essential prerequisites for responsible AI deployment in orthopaedics, emphasizing that the treating clinician must retain ultimate responsibility for patient care regardless of the degree of algorithmic assistance. This principle has direct implications for informed consent processes, which must accurately convey the human-supervised — rather than autonomous — nature of AI-assisted interventions.

Ethical frameworks for AI in orthopaedics have been proposed by Kaya Bicer et al. (2023) and Kiwinda et al. (2025), emphasizing beneficence, non-maleficence, autonomy, and justice as organizing principles for responsible integration. These considerations are particularly salient for smart implants and digital twins — technologies that generate continuous patient data, raising questions about data ownership, consent frameworks, cybersecurity, and appropriate commercialization of patient-generated health information.

### 4.4. Implications for Healthcare and Society

Beyond individual clinical outcomes, the integration of artificial intelligence in orthopaedics carries important implications for healthcare systems, resource allocation, and equity of care delivery. The potential of AI to reduce diagnostic error rates in musculoskeletal imaging may contribute to improved clinical decision-making and more consistent diagnostic performance (Rajpurkar et al., 2022). By improving diagnostic consistency and enabling earlier intervention, AI systems may contribute to more efficient patient pathways and reduced burden on specialist services (O'Malley et al., 2026).

From a health system perspective, AI-assisted diagnostic tools and automated reporting systems may alleviate workforce pressures, particularly in settings with limited access to experienced radiologists or orthopaedic specialists. This is of particular relevance in public healthcare systems, where increasing demand for imaging and surgical procedures is not always matched by proportional workforce expansion (Misir & Yuce, 2025). In this context, AI has the potential to support task redistribution and improve operational efficiency without replacing clinical decision-making (O'Malley et al., 2026).

However, the economic implications of AI adoption remain complex. While certain applications — such as automated image analysis — may reduce per-case costs over time, high initial investment costs associated with robotic surgical systems and advanced digital infrastructure may limit accessibility (Aggarwal et al., 2024; Misir & Yuce, 2025). This creates a risk of uneven implementation, where well-resourced institutions benefit disproportionately, potentially widening existing disparities in healthcare quality and access (Misir & Yuce, 2025).

Equity considerations are further reinforced by the dependence of AI systems on training data. Models developed predominantly in high-income settings may not generalize effectively to diverse populations, raising concerns regarding algorithmic bias and unequal performance across demographic groups (Siddiqui et al., 2024). Addressing these challenges requires further external validation and careful clinical integration across varied healthcare environments (Andreacchio & Mah, 2025).

At a broader societal level, the increasing integration of AI into orthopaedic workflows may contribute to a shift in the role of the clinician — from primary decision-maker toward a hybrid model combining clinical expertise with algorithm-supported judgment (Rajpurkar et al., 2022). This transition necessitates adaptation in medical education, regulatory frameworks, and professional standards, ensuring that clinicians remain equipped to critically interpret AI outputs and maintain responsibility for patient care (Kiwinda et al., 2025).

Overall, while artificial intelligence presents clear opportunities for improving efficiency, consistency, and scalability of orthopaedic care, its implementation must be carefully managed to ensure that technological advancement translates into equitable and system-wide benefit.

### 5. Conclusions

This narrative review demonstrates that artificial intelligence has achieved meaningful, evidence-supported utility across orthopaedic diagnostics and surgical planning: deep learning models achieve clinician-level or superior accuracy in fracture detection and osteoarthritis grading (Nowroozi et al., 2024; Zhao et al., 2025); AI-integrated preoperative planning systems improve implant sizing predictions (Altahtamouni et al., 2026); and robotic-assisted surgery consistently reduces mechanical alignment outliers (Mostafa et al., 2025). Emerging frontiers through 2026 — including smart implants, digital twins, LLM-assisted clinical documentation, and federated learning frameworks — suggest that AI's role will continue to expand well beyond diagnostic imaging toward a more holistic integration into the entire perioperative continuum.

Nevertheless, translation from algorithmic performance to equitable patient benefit requires addressing fundamental challenges in external validation, algorithmic transparency, data governance, regulatory harmonization, and ethical deployment. Future research should prioritize prospective multi-center clinical trials with patient-centered endpoints; development of explainable and uncertainty-aware AI systems; privacy-preserving federated learning frameworks; and health economic analyses assessing cost-effectiveness across diverse healthcare systems.

As AI continues to mature and clinical adoption accelerates, the orthopaedic community has both an opportunity and a responsibility to shape its integration in a manner that is scientifically rigorous, ethically grounded, and equitably directed — ensuring that technological progress serves all patients, regardless of institutional setting, socioeconomic status, or geographic location.

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