

REVIEW ARTICLE

An artificial intelligence-assisted comprehensive clinical decision-making guide for total knee arthroplasty

Puja Ravi¹, Rahul Kumar^{2*}, Kyle Sporn³, Nasif Zaman⁴, and Alireza Tavakkoli⁴¹Department of Biology, University of Michigan, Ann Arbor, Michigan, United States of America²Department of Medicine, T.H. Chan School of Medicine, University of Massachusetts, Worcester, Massachusetts, United States of America³Department of Medicine, SUNY Upstate Medical University, Norton College of Medicine, Syracuse, New York, United States of America⁴Human–Machine Perception Laboratory, Department of Computer Science and Engineering, College of Engineering, University of Nevada, Reno, Nevada, United States of America

Abstract

With the demand for total knee arthroplasty (TKA) projected to reach 3.48 million surgeries annually by 2030, leveraging artificial intelligence (AI) is crucial for optimizing outcomes and healthcare efficiency. Hence, we present a systematic approach for integrating AI and machine learning approaches into clinical decision-making for TKA and other orthopedic interventions. This guide outlines evidence-based protocols for various scenarios, from comprehensive pre-operative assessment and risk stratification using natural language processing and biomarker analysis, to intraoperative decision support with computer vision for optimal component positioning. It also covers the detection of early osteoarthritis in athletes through molecular biomarkers and advanced imaging, as well as systematic post-operative monitoring for complication prevention. This guide encompasses chronic pain management, population health screening for early osteoarthritis, acute knee injury assessment in the emergency room, and complex revision TKA planning. Essential technological integrations include ResNet for imaging analysis, Claude 3 for complex reasoning, OpenCV/MediaPipe for biomechanical evaluation, and GPT-4 Turbo for documentation. For the safe, ethical, and efficient application of AI—and ultimately for the improvement of individualized orthopedic care—this framework places a strong emphasis on thorough clinical validation, regulatory compliance, bias mitigation, and economic considerations.

Keywords: Total knee arthroplasty; Artificial intelligence; Machine learning; Clinical decision-making; Orthopedic interventions; Risk stratification; Post-operative monitoring; Personalized orthopedic care

***Corresponding author:**Rahul Kumar
(Rahul.Kumar5@umassmed.edu)

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1. Introduction

Today, sports medicine practitioners require systematic approaches for integrating artificial intelligence (AI) and machine learning (ML) technologies into clinical

decision-making processes.¹ We designed these guidelines as a starting point for sports medicine practitioners on the ethical use of AI and ML technologies in clinical practice, providing specific protocols for common clinical scenarios with particular emphasis on total knee arthroplasty (TKA) and orthopedic interventions.²

According to patient reports, TKA has a significant impact on pain relief, functional restoration, and quality of life, making it one of the most economical and consistently successful surgical procedures in orthopedics.³ For patients with degenerative osteoarthritis or end-stage tricompartmental osteoarthritis, TKA yields consistent results.⁴ Given that millions of Americans suffer from osteoarthritis, a progressive disease marked by progressive degeneration and loss of articular cartilage, the knee is most frequently affected.⁵ Since the United States performs about 400,000 primary TKA procedures a year and the demand is expected to reach 3.48 million procedures by 2030, AI technologies must be systematically integrated to improve clinical outcomes and the effectiveness of healthcare delivery.⁶

Degenerative joint disease's pathophysiology poses diagnostic and therapeutic challenges.⁷ To provide a comprehensive and understandable evaluation of joint health across biological levels, from molecular pathways to tissue-level alterations, a systems medicine approach to diagnosing degenerative joint disease integrates multiple data streams.⁸ Physicians can better monitor therapeutic responses, stratify patients according to disease subtypes, predict progression trajectories, and identify disease early by integrating data from clinical assessment, quantitative imaging parameters, synovial fluid analysis, and circulating biomarkers.⁹

This clinical decision-making guide provides evidence-based protocols for scenarios encountered in sports medicine practice, offering practitioners clear, systematic approaches emphasized by AI technologies for diagnosis, treatment planning, and patient management across the complete spectrum of orthopedic care¹⁰ (Table 1).

2. Clinical decision-making framework with AI

2.1. Scenario-based clinical decision-making framework

2.1.1. Scenario 1: Comprehensive pre-operative TKA assessment and risk stratification

A comprehensive pre-operative assessment and risk stratification were conducted for a 65-year-old carpenter presenting with progressive knee pain and functional limitation.¹¹ The process begins with Phase 1, an initial

clinical assessment with AI-driven data integration. Natural language processing (NLP) using Bidirectional Encoder Representations from Transformers for Biomedical Text Mining (BioBERT) analyzes clinical notes to extract relevant history, including prior interventions, treatments, joint replacements, arthroscopic procedures, and other knee surgeries. This is integrated with clinical evaluation of surgical scars, retained hardware, and knee instability patterns to inform the surgical approach. If complications from previous surgeries are detected, a comprehensive surgical risk assessment and alternative approach planning are initiated.

In Phase 2, the advanced biomarker analysis with ML interpretation employs the extreme gradient boosting algorithm for multivariable biomarker pattern recognition. Biomarkers such as C-terminal telopeptides of Type II collagen (CTX II) are analyzed in correlation with Kellgren–Lawrence grading, while cartilage oligomeric matrix protein (COMP) levels are evaluated against patient age, body mass index, pain levels, and interleukin 1 beta (IL-1 β) concentrations.¹² In addition, inflammatory profiling assesses IL-1 β as a key mediator through nuclear factor kappa B signaling and evaluates matrix metalloproteinase (MMP)-3 and MMP-13 for the degradation of Type II collagen and proteoglycans. If the CTX II level exceeds 500 ng/mmol creatinine, COMP concentration exceeds 17 U/L, and MMP levels are elevated, the patient is classified with a high cartilage degradation score, prompting prioritization of surgical intervention. If IL-1 β exceeds 5 pg/mL with elevated inflammatory markers, an active inflammatory state is indicated, necessitating optimized pre-surgical medical management.

In Phase 3, the comprehensive imaging analysis with computer vision incorporates ResNet-based imaging analysis with dual attention mechanisms. Automated measurements include hip-knee-ankle angle (optimal: 3° varum to 3° valgum), frontal femoral component angle (2–7° valgus), frontal tibial component angle (perpendicular), and lateral tibial component positioning.⁹ Advanced imaging modalities, such as T2 mapping magnetic resonance imaging (MRI), dual-energy computed tomography (CT), and ultrasound elastography, further characterize the integrity of cartilage, bone, and soft tissue. Clinical decision-making integrates these findings: for instance, a hip-knee-ankle angle >3° varus increases surgical complexity and may warrant constrained implants and extensive soft-tissue releases; significant cartilage degradation on T2 mapping accelerates surgical timelines; and compromised bone quality on dual-energy CT prompts a modified fixation strategy.

Finally, in Phase 4, the comprehensive risk prediction modeling leverages ensemble learning with random

Table 1. Summary of clinical scenarios

Clinical phase	Scenario	Objective	Artificial intelligence technology	Clinical outcome
Pre-operative	Comprehensive pre-operative assessment	Stratify patient risk and predict outcomes before surgery	Natural language processing, biomarker analysis	Personalized risk profiles and optimized treatment plans
	Surgical planning and prosthesis selection	Optimize component sizing and placement for individualized anatomy	Computer vision, three-dimensional imaging	Improved implant fit, reduced revision rates, and enhanced joint function
Intraoperative	Intraoperative decision support	Provide real-time guidance to surgeons for precise implant alignment	Computer vision, sensor data	Minimized surgical errors and maximized procedural accuracy
Postoperative	Post-operative complication monitoring	Systematically track patients to identify and prevent complications	ML, wearable sensors	Early detection of issues, such as infections or instability, enables timely intervention
	Rehabilitation and recovery	Personalize physical therapy protocols and monitor patient progress	Computer vision, biomechanics analysis	Accelerated recovery, reduced rehabilitation time, and improved functional scores
Patient management	Chronic pain management	Identify pain patterns and recommend targeted interventions	ML, predictive analytics	More effective pain control and enhanced patient quality of life
Diagnostics	Early osteoarthritis detection	Screen high-risk individuals for early signs of osteoarthritis	Molecular biomarkers, advanced imaging	Proactive, non-surgical interventions to slow disease progression
	Acute knee injury assessment	Facilitate rapid and accurate diagnosis in emergency settings	Computer vision, diagnostic algorithms	Expedited treatment and improved outcomes for acute injuries
Revision surgery	Complex revision total knee arthroplasty planning	Plan for complex revision surgeries by analyzing a wide range of data	Large language models, data synthesis	Comprehensive, data-driven surgical strategies for challenging cases
Population health	Population health screening	Identify at-risk populations for osteoarthritis on a large scale	Predictive analytics, public health data	Proactive public health initiatives and resource allocation
Long-term monitoring	Long-term implant survivorship	Predict the lifespan of implants based on patient-specific data	ML, data modeling	Enhanced patient education and proactive management of implant wear
Documentation and education	Surgical documentation and reporting	Automate the creation of detailed surgical and post-operative reports	Large language models	Reduced administrative burden and improved consistency in medical records

Abbreviation: ML: Machine learning

forest, extreme gradient boosting, and neural networks to integrate patient demographics, comorbidities, pre-operative functional scores (Western Ontario and McMaster Universities Osteoarthritis Index, Knee Society Score, Short Form 36 health survey), imaging parameters, and biomarker profiles. The model outputs predictions for 1-, 5-, 10-, and 15-year implant survival, stratifies risks for major complications such as infection, thrombosis, and loosening, and forecasts functional improvement trajectories, return-to-work timelines, and activity modification recommendations.

2.1.2. Scenario 2: Intraoperative decision support for optimal component positioning

In Scenario 2, intraoperative decision support is utilized to ensure optimal component positioning during a TKA procedure.

In Phase 1, real-time surgical navigation with advanced computer vision integrates OpenCV with MediaPipe for comprehensive pose estimation, enabling optimized surgical approaches.¹⁰ Along with real-time tissue quality assessment for the best closure planning, this also includes evaluation of the medial parapatellar approach with quadriceps tendon preservation, as well as midvastus and subvastus approaches based on patient anatomy. Component positioning is continuously monitored, with anterior femoral notching prevention kept below a 3 mm threshold, frontal tibial component aligned perpendicularly, and frontal femoral component angles aimed at 2–7° valgus. Immediate guidance is provided by an integrated alert system, which automatically recommends corrective measures if the anterior notching risk is identified, the tibial cut varus exceeds 3°, or the FFC angle deviates more than 1° from the target.

In Phase 2, the advanced gap balancing with AI-powered sensor integration employs multi-sensor AI algorithms to process force, angle, and tissue tension measurements. Gap balancing follows a flexion gap first approach to achieve rectangular gaps, complemented by extension gap balancing through optimized ligament releases, and measured resections guided by transepicondylar and anteroposterior axis landmarks.¹⁰ Real-time feedback systems provide continuous monitoring of flexion gap symmetry with millimeter precision, dynamic extension gap balance assessment, and automated ligament release recommendations. If gap asymmetry exceeds 2 mm, or if rectangular gaps and soft-tissue tension balance are not achieved, the system provides targeted release protocols and automated component repositioning guidance.¹³

In Phase 3, the alignment and rotation of component optimization uses ML and sophisticated computer vision to find anatomical landmarks. Alignment with the transepicondylar, anteroposterior, and posterior condylar axes is confirmed by rotational assessment protocols. Automated quality assurance systems use the “no thumb” test to evaluate patellar tracking, prevent component overhang, and identify malrotation $>3^\circ$ with prompt correction alerts. These precautions also lessen the chance of arthrofibrosis, patellofemoral instability, and anterior knee pain.

In Phase 4, the comprehensive stability and function assessment integrates intraoperative sensor data with predictive modeling. Stability evaluation protocols assess the range of motion from full extension to flexion, verify ligament balance throughout the flexion arc, and check for maltracking in patellar tracking. Based on intraoperative findings, predictive models subsequently produce postoperative recovery forecasts that include expected range of motion, long-term stability trajectories, and customized recovery timelines.¹⁴

In Phase 5, the component rotation and alignment optimization use advanced computer vision combined with ML to recognize anatomical landmarks and ensure accurate rotational alignment. The protocol includes transepicondylar axis identification and verification, anteroposterior axis correlation analysis, and posterior condylar axis assessment for precise femoral component rotation. Quality assurance systems are integrated to automatically detect malrotation $>3^\circ$ and provide immediate correction alerts. Additional safeguards include patellar tracking verification through the “no thumb” test, automated detection of component overhang, and preventive strategies against malpositioning. Real-time monitoring systems also function to mitigate complication risks by reducing the likelihood of anterior knee pain, patellofemoral joint instability, and arthrofibrosis.

In Phase 6, the comprehensive stability and function assessment employs integrated sensor systems with predictive modeling to evaluate intraoperative and postoperative outcomes.¹⁴ Stability is measured through range of motion assessment from full extension to deep flexion, ligament balance verification across the flexion arc, and patellar tracking evaluation for maltracking detection. Predictive models then forecast postoperative range of motion, estimate long-term joint stability based on component positioning, and provide individualized recovery timelines tailored to patient-specific intraoperative findings.

2.1.3. Scenario 3: Comprehensive early osteoarthritis detection in athletes

This scenario examined a 28-year-old professional soccer player presenting with mild knee discomfort and performance decline.

In Phase 1, the comprehensive molecular biomarker analysis applies ML algorithms for biomarker pattern recognition and correlation. Cartilage degradation is evaluated through CTX II analysis using sport-specific reference ranges adjusted for training load, COMP levels interpreted relative to age and activity, and Type II collagen fragment analysis for early cartilage stress detection.¹⁵ Inflammatory cascades are examined through IL-1 β , tumor nuclear factor alpha, and nuclear factor kappa B pathway markers, alongside matrix metalloproteinase profiling (MMP-3, MMP-13) for proteoglycan degradation. Advanced biomarker integration includes cyclooxygenase-2 expression, induced nitric oxide synthase assessment, and synovial fluid microRNA profiling for early joint degeneration. Clinical decisions follow a structured matrix: if CTX II level rises $>50\%$ above baseline with normal COMP, acute cartilage stress is suspected and immediate training modification is indicated; if CTX II and COMP are both elevated with positive inflammatory markers, progressive degeneration is confirmed, prompting comprehensive intervention; and if MMPs are elevated without radiographic changes, subclinical cartilage breakdown is diagnosed, warranting close monitoring and preventive strategies.

In Phase 2, advanced imaging with quantitative analysis integrates multimodal imaging with AI-enhanced interpretation. T2 mapping MRI establishes baseline relaxation times for hydration assessment, evaluates regional cartilage compartments, and tracks longitudinal changes correlated with biomarkers.¹⁶ Ultrasound elastography provides real-time evaluation of tissue stiffness under sport-specific protocols, quantifies synovial inflammation, and evaluates cartilage mechanical integrity during movement. Dual-energy CT offers subchondral

bone assessment for early remodeling, detects osteophytes prior to radiographic visibility, measures joint space with sub-millimeter precision, and identifies bone marrow lesions. Imaging-based decisions are stratified: T2 values above 40 ms in weight-bearing regions indicate early cartilage degeneration and require biomarker correlation; elastography stiffness exceeding 30 kPa suggests an inflammatory response that requires anti-inflammatory intervention; and subchondral changes on dual-energy CT indicate bone involvement necessitating joint protection strategies.¹⁷

In Phase 3, functional and biomechanical assessments integrate wearable sensor data with ML to analyze gait and sport-specific movements. Real-time biomechanical assessments evaluate joint loading, detect compensatory movement patterns, and correlate performance metrics with joint health indicators. Training load integration allows continuous monitoring of exercise intensity, recovery patterns, and biomarker responses. Predictive models then forecast performance decline, cumulative stress effects, and injury risk, enabling proactive modifications to training protocols that protect joint health and prolong athletic performance.¹⁷

2.1.4. Scenario 4: Comprehensive postoperative TKA monitoring and complication prevention

This scenario involves systematic surveillance of patients from the immediate post-operative period through lifelong follow-up.

Immediate post-operative monitoring (Phase 1; 0–6 weeks) utilizes smart implant integration with long short-term memory networks for temporal pattern analysis. Data streams include continuous activity level monitoring against baseline, range of motion tracking with automated milestone assessment, weight-bearing progression through loading pattern analysis, and implant stability monitoring through micro-motion detection.¹⁸ Complication risk is simultaneously assessed with predictive models for deep vein thrombosis using activity and physiological data, infection risk stratification through temperature and inflammatory markers, and wound healing assessment using objective tools. Automated alerts are built into the system: if activity level falls below 25% of baseline at 2 weeks, enhanced rehabilitation protocols are activated; if asymmetric loading persists beyond 4 weeks, gait analysis and correction are initiated; and if range of motion plateaus, intensive therapy protocols are implemented.

Early recovery monitoring (Phase 2; 6 weeks–6 months) integrates multimodal data with predictive analytics. Comprehensive assessments combine patient-reported outcome measures with objective data to track functional

milestones, analyze pain patterns relative to activity, and use sleep quality as a recovery indicator. Complication detection protocols include early warnings for aseptic loosening using implant sensors and imaging correlation, infection surveillance through multi-parameter analysis, stiffness prediction and prevention, and heterotopic ossification risk assessment.¹⁸ Rehabilitation optimization strategies feature personalized therapy adjustments, exercise compliance monitoring with automated feedback, individualized goal setting, and return to activity timeline optimization.

Long-term monitoring (Phase 3; 6 months–lifetime) applies comprehensive data integration with ML approaches for predictive modeling of outcomes. Implant survivorship is tracked through continuous monitoring, wear pattern analysis with advanced imaging, precision measurement for component migration, and revision risk stratification. Functional outcome tracking extends to activity maintenance, sports participation optimization, quality of life metrics correlated with objective data, and patient satisfaction monitoring with intervention triggers. Complication prevention focuses on late infection surveillance, periprosthetic fracture risk assessment using bone quality monitoring, biomechanical analysis to protect adjacent joints, and optimized revision planning guided by predictive models.

2.1.5. Scenario 5: Complex revision TKA planning with AI integration

This scenario addresses the management of failed primary TKA complicated by multiple adverse outcomes.

During Phase 1, the comprehensive failure analysis employs multimodal AI analysis to determine failure mechanisms. Implant assessment protocols include component positioning evaluation using historical surgical data, wear pattern identification through advanced imaging, loosening mechanism determination from radiographic progression, and correlation of patient-specific risk factors with failure patterns.¹⁹ Bone stock assessment is performed using dual-energy CT for quantitative evaluation of bone loss, three-dimensional (3D) reconstruction for mapping defects, bone quality analysis for revision planning, and growth factor profiling to assess healing potential. Soft-tissue evaluation incorporates ligament integrity assessment through advanced imaging, scar tissue quantification to guide surgical planning, vascular assessment for healing capacity, and the rule out of infection through comprehensive diagnostics.¹⁹

In Phase 2, the infection evaluation and management integrate AI-enhanced diagnostics with Musculoskeletal Infection Society criteria.²⁰ The comprehensive infection

assessment includes evaluation of sinus tracts, pathogen identification, multipoint tissue sampling analyzed with AI pattern recognition, and laboratory parameters such as erythrocyte sedimentation rate >30 mm/hr and C-reactive protein level >10 mg/L.²¹ Synovial fluid is analyzed using automated leukocyte counts and neutrophil percentage, while joint aspiration provides the highest specificity for confirmation.²² Advanced diagnostics extend to histologic evaluation with automated neutrophil counting (>5 neutrophils per high-power field), microorganism identification with antimicrobial susceptibility profiling, and infection localization using positron emission tomography-CT.²³ Based on these findings, treatment strategy optimization is achieved by integrating microbiologic data, imaging evidence, and patient-specific comorbidity profiles, ensuring tailored surgical and antimicrobial management for revision TKA.²⁴

In Phase 3, surgical planning and execution in revision TKA employs computer-aided design/computer-aided manufacturing integration with AI-enhanced custom implant design. Advanced surgical planning incorporates patient-specific implant modeling through 3D printing, virtual surgical simulations with outcome prediction, bone graft optimization based on defect analysis, and component selection guided by AI-driven compatibility assessments.²⁵ Intraoperatively, real-time navigation with revision-specific protocols is used, alongside automated cutting guides for bone preparation, soft-tissue balancing tailored to the complexity of revision procedures, and quality assurance protocols designed to address the unique challenges of revision procedures.²⁶

2.1.6. Scenario 6: Emergency department acute knee injury assessment

This scenario addresses the management of acute traumatic knee injuries requiring rapid diagnostic evaluation.

In Phase 1, the rapid triage and initial assessment apply automated decision support systems enhanced by the Ottawa Knee Rules, incorporating trauma-specific parameters, mechanism of injury pattern recognition, pain severity analysis, functional correlation, and AI-assisted stability testing.²⁷ Imaging decision support tools generate automated recommendations, prioritize imaging allocation, suggest alternative modalities based on suspected pathology, and incorporate cost-effectiveness analyses.²⁸

During Phase 2, advanced imaging analysis uses convolutional neural networks for rapid fracture detection with 95% sensitivity and 92% specificity, enabling classification of fracture type, severity, and alignment for stability assessment.²⁹ Bone quality is evaluated for

treatment planning, and advanced imaging integration includes MRI for soft-tissue injuries, ultrasound for effusion evaluation, CT for complex fractures, and multiplanar reconstruction for comprehensive assessment. A rapid reporting system automatically generates preliminary results within 10 min, issues critical finding alerts, triggers specialist consultations for severe injuries, and classifies treatment urgency with time-sensitive protocols.³⁰

2.1.7. Scenario 7: Chronic pain management and functional restoration post-TKA

This scenario addresses patients experiencing persistent pain six months after surgery, despite normal standard imaging.

During Phase 1, comprehensive pain characterization leverages NLP for pain description analysis using validated scales, recognition of temporal pain patterns, correlation with activity triggers, and evaluation of medication responses.³⁰ Psychological factors are also integrated, including depression and anxiety screening, pain catastrophizing assessment, sleep quality evaluation, and social support measurement to predict recovery outcomes. Advanced analysis further identifies neuropathic pain components, central sensitization through quantitative sensory testing, pharmacogenomic-based pain medication optimization, and coordination of multidisciplinary care.³¹

In Phase 2, advanced diagnostic evaluation combines multimodal imaging and biomechanical assessment to uncover hidden pain sources.³¹ Imaging includes high-resolution MRI, single-photon emission CT, and CT for metabolic activity and infection assessment, ultrasound elastography for soft-tissue integrity, and dynamic imaging for motion-related abnormalities. Biomechanical analysis incorporates gait evaluation, motion capture of joint mechanics, electromyography-based muscle activation profiling, and balance testing for fall risk. Neurological assessment is performed using nerve conduction studies, sensory testing, brain imaging for central pain processing, and autonomic function evaluation. Together, these data support personalized interventions to restore function and improve quality of life.

2.1.8. Scenario 8: Population health screening for early osteoarthritis

This scenario outlines a community-wide screening model for the early detection of osteoarthritis in at-risk groups.

During Phase 1, risk assessment and stratification utilize population health analytics with ML techniques to integrate demographic, genetic, environmental, and lifestyle risk factors. Screening incorporates validated

questionnaires with AI interpretation, standardized physical exams, biomarker point-of-care testing, and portable ultrasound imaging.³² Risk stratification protocols categorize individuals as low, moderate, high, or very high risk, aligning them with tailored monitoring, preventive, or specialist referral pathways.

In Phase 2, point-of-care diagnostic implementation deploys portable diagnostic devices with AI-powered analysis. Biomarker testing includes fingerstick blood for inflammation and cartilage degradation markers, saliva testing for stress-related mediators, urine assays for collagen breakdown, and multi-analyte joint health panels. Imaging integration features handheld ultrasound, portable X-ray with automated interpretation, smartphone-based imaging with ML enhancement, and wearable sensors for continuous joint monitoring. Immediate risk assessment provides real-time lifestyle counseling, automated referral coordination, and AI-optimized follow-up scheduling for surveillance.³²

2.2. AI technologies and tools

Advanced technology integration for total clinical care expands these applications by embedding large language models to enhance clinical documentation, communication, and decision support. GPT-4 Turbo and related large language models enable a more robust clinical dialogue, real-time multimodal data fusion, and literacy and culture-aware patient education, completing the AI-augmented orthopedic care continuum from prevention through revision.

In terms of advanced clinical documentation systems, Azure OpenAI Service deployment of GPT-4 Turbo provides Health Insurance Portability and Accountability Act capabilities for unambiguous clinical documentation.³³ Improved medical text analysis performance in research is reported with micro F1 scores of 0.838 in clinical identification from electronic health records (EHRs).³⁴ The system's enhanced reasoning abilities enable it to generate holistic, individualized medical documentation with patient-specific details and clinical intricacy.³⁵

The full range of orthopedic care is covered by comprehensive documentation applications. Comprehensive operative reports that cover the rationale behind approach selection, component specifications, alignment parameters, and technical difficulties encountered during TKA procedures are produced by automated surgical procedure documentation.³⁶ The process is further improved by patient assessment integration, which simultaneously performs automated correlation analyses and records comprehensive history and physical examination findings, such as pain assessment, functional evaluation, prior

treatments, and surgical history.³⁶ Building on this basis, the creation of treatment plans integrates patient-specific data, evidence-based recommendations, and the need for multidisciplinary coordination to produce comprehensive, customized protocols. The automated creation of rehabilitation schedules, monitoring procedures, and expert referral recommendations also optimizes follow-up care coordination, guaranteeing continuity of care.

At the same time, sophisticated multilingual capabilities improve patient education and communication by allowing the development of comprehensive educational resources in more than 95 languages to cater to various patient populations.³⁷ Personalization features increase accessibility and engagement by tailoring these resources to patients' literacy levels, cultural backgrounds, and particular concerns.³⁷ Appendix A1 contains the complete framework that supports these features.³⁸

Advanced reasoning systems improve clinical decision-making more than documentation. Deployed on Amazon Bedrock, Claude 3 provides advanced decision support with multi-turn dialogue skills and contextual interpretation of complex medical literature.³⁸ In multifactorial clinical scenarios, its capabilities enable nuanced analysis, producing evidence-based recommendations that supplement the expertise of physicians.³⁹ Through the integration of various clinical parameters, imaging findings, and laboratory results for reliable differential diagnosis grading, the system facilitates a wide range of clinical applications, including multifactor diagnostic support. Analyzing the available data in conjunction with patient-specific variables also aids in the optimization of treatment protocols by producing personalized treatment recommendations and outcome forecasts. Risk assessment integration further refines decision-making by evaluating surgical risks, comorbid conditions, and individualized patient profiles, while literature integration ensures that the latest medical research is continuously synthesized into patient-specific recommendations in real time.⁴⁰

2.2.1. ResNet architecture implementation for medical image classification

In medical image classification tasks, the advanced imaging analysis framework achieves an accuracy rate of 0.940 by utilizing ResNet architectures with dual attention mechanisms.⁴¹ The method is extremely useful for thorough pre-operative evaluation and postoperative monitoring due to its high degree of precision.⁴¹ Through focused analysis of important anatomical structures and pathological changes, the system improves interpretability and performance by integrating attention mechanisms,

guaranteeing clinically significant insights for orthopedic decision-making.⁴²

2.2.2 Comprehensive imaging applications

The comprehensive imaging applications framework offers robust instruments for orthopedic evaluation in various clinical stages. The radiographic analysis protocol can automatically measure essential parameters, such as hip-knee-ankle angles, component positioning, and alignment verification with sub-degree precision.⁴³

In addition, the MRI interpretation system enables quantitative analysis for the systematic assessment of ligament status, bone marrow lesions, synovial inflammation, and cartilage integrity.⁴³ Using instantaneous feedback systems to confirm component positioning, alignment, and overall quality assurance, real-time guidance during surgery aids in surgical precision.⁴³ Longitudinal monitoring makes it easier to automatically compare serial imaging studies for continued care, tracking the progression of the disease, and identifying complications.

2.2.3. OpenCV and MediaPipe integration for real-time biomechanical analysis

Accurate, real-time movement analysis in clinical and rehabilitation settings is now possible thanks to recent developments in computer vision. Clinicians and researchers can objectively track joint angles, gait patterns, and compensatory strategies with high temporal resolution by integrating OpenCV with MediaPipe.⁴⁴ This synergy transforms subjective assessment into quantifiable biomechanical data, offering immediate feedback that enhances rehabilitation outcomes, improves exercise technique, and reduces the risk of reinjury.⁴⁵ The following examples demonstrate how adaptable this framework is to sports medicine, injury prevention, and rehabilitation.

OpenCV and MediaPipe have extensive biomechanical applications in performance optimization, injury prevention, and rehabilitation. Real-time evaluation of gait patterns, joint angles, and movement symmetry is made possible by the gait analysis protocol, which also automatically identifies compensatory strategies that might be signs of dysfunction. Exercise form evaluation offers automated rehabilitation technique monitoring, providing real-time feedback and remedial guidance to guarantee correct execution. By examining entire movement patterns to evaluate injury risk and general movement quality, functional movement screening broadens the scope even more. Last but not least, sports-specific evaluations enable in-depth examination of athletic motions, assisting with return-to-play assessments and performance enhancement.

2.2.4. NLP for comprehensive medical text analysis

Clinicians are finding it increasingly challenging to stay up-to-date with the rapidly expanding body of biomedical knowledge. For overcoming this difficulty, NLP models like BERT and its domain-specific equivalent, BioBERT, offer strong instruments. These models make literature reviews, automated coding, and quality assurance easier by facilitating the high-accuracy extraction, classification, and synthesis of clinical text. The following extensive clinical applications demonstrate how their proven superiority in biomedical text mining makes them essential for incorporating medical literature into decision-making workflows.

With F1 score improvements of 2.80% over standard BERT, the use of BERT and its domain-specific counterpart, BioBERT, has improved medical text analysis by showcasing exceptional performance in biomedical text mining.⁴⁶ These models are essential tools for organizing unstructured medical data, as they are highly effective at automating literature reviews, medical coding optimization, and clinical note analysis.⁴⁶ Among their many uses are the automated coding and classification of documents to extract important clinical information, the systematic review and summarization of research literature with evidence grading and recommendation generation, and the optimization of International Classification of Diseases, Tenth Revision, and Current Procedural Terminology coding with accuracy verification and compliance monitoring. In addition, they facilitate quality assurance by automatically reviewing clinical documentation to guarantee accuracy, completeness, and compliance with clinical guidelines.⁴⁷

2.3. Comprehensive clinical scenarios and evidence-based AI solutions

Building on these features, evidence-based AI solutions can be produced by directly applying BERT and BioBERT models to intricate clinical situations.

2.3.1. Scenario 9: Periprosthetic joint infection diagnosis and management

This scenario involves a 68-year-old patient with suspected TKA infection eight months post-surgery. Phase 1 is a comprehensive diagnostic evaluation. The comprehensive diagnostic evaluation for periprosthetic joint infection involves a multi-parameter approach guided by the Musculoskeletal Infection Society criteria.⁴⁸ The clinical assessment protocol begins with a systematic evaluation of sinus tract presence communicating with the prosthesis,⁴⁸ followed by comprehensive pathogen isolation from multiple tissues and fluid samples.⁴⁸ Laboratory parameters include elevated erythrocyte sedimentation rate >30 mm/h and C-reactive protein >10 mg/L,⁴⁸ as

well as synovial fluid analysis with automated leukocyte count and neutrophil percentage assessment.⁴⁸ Joint aspiration remains the highest specificity for infection confirmation,⁴⁸ complemented by histologic analysis with automated neutrophil counting (>5 neutrophils/high-power field)⁴⁸ and microorganism identification with antimicrobial susceptibility testing. Advanced imaging, including positron emission tomography-CT, is integrated for infection localization.

Phase 2, the treatment strategy optimization for periprosthetic joints, leverages AI-powered treatment selection using the Arthroplasty Outcome Study classification system. Based on infection type, tailored protocols are applied to improve patient outcomes.⁴⁹ These include:

- (i) Type 1 (positive intraoperative culture): Antibiotic therapy optimization
- (ii) Type 2 (early postoperative infection): Debridement, antibiotics, and retention protocols
- (iii) Type 3 (acute hematogenous infection): Aggressive debridement with prosthesis retention
- (iv) Type 4 (late chronic infection): Comprehensive revision arthroplasty planning.

Predicting treatment success in the management of periprosthetic joint infections requires sophisticated modeling that incorporates a number of biological and clinical factors. To enable customized outcome estimation, success rates are predicted according to the type of infection, the causative organism, and patient-specific factors. While surgical strategies are guided by predictive algorithms that correlate intervention choices with expected recovery trajectories, antibiotic regimens are optimized through pharmacokinetic modeling to ensure effective dosing and therapeutic precision. Long-term monitoring procedures are also created to monitor patient development, identify recurrences early, and promote long-term functional results.

2.3.2. Scenario 10: Comprehensive complication prevention and management

This scenario outlines a systematic approach to preventing and managing TKA complications. AI-driven risk assessment protocols that consider surgical technique, component selection, and bone quality improve the prevention and management of periprosthetic fractures. Fractures are managed according to their type: patellar fractures, which occur in 0.2–15% of unresurfaced cases, require risk factor analysis and customized treatment optimization,⁵⁰ tibial fractures, which occur in 0.5–1% of cases, require careful evaluation of component stability and fixation requirements,⁵⁰ and distal femur fractures, which

occur in 1–2% of cases, require component constraint evaluation and fracture fixation planning.⁴⁹ Preventive measures also prioritize optimizing bone quality to lower fracture risk and monitoring anterior femoral notching to keep thresholds below 3 mm.⁵⁰

Another serious issue is aseptic loosening, which is managed with thorough monitoring and preventative measures. Osteolysis detection and assessment of macrophage-induced inflammatory responses are used to monitor pathophysiological mechanisms.⁵⁰ Pain pattern analysis is used to evaluate clinical presentation, separating symptoms that occur at rest from those that occur during weight-bearing activity. While prevention protocols concentrate on reducing wear debris and optimizing implant selection to ensure long-term stability, radiographic monitoring includes automated detection of radiolucent spaces and implant displacement.⁵⁰

Since deep vein thrombosis affects up to 15% of patients and is symptomatic in 2.3% of cases, thromboembolism prevention is equally important.⁵⁰ Risk can be reduced by optimizing anticoagulation protocols with medications like aspirin, rivaroxaban, dabigatran, or apixaban.⁵¹ Continuous monitoring of mobility and activity levels also helps identify at-risk patients early and prevents thrombotic events by intervening promptly.

2.3.3. Scenario 11: Comprehensive rehabilitation and functional recovery

This scenario describes a systematic rehabilitation protocol for optimal TKA recovery. Phase 1 is an immediate post-operative rehabilitation (0–6 weeks) with continuous monitoring using smart implant integration. After a total knee replacement, rehabilitation consists of a number of structured elements intended to speed healing and avoid complications. Until the surgeon gives the all-clear, protected weight bearing with crutches or a walker is maintained, and post-operative muscle weakness is addressed with targeted quadriceps strengthening.⁵¹ To promote activity resumption and lower the risk of complications, a range of motion recovery protocol is used, with a minimum objective of reaching 0–110°, and is backed by several weeks of supervised physical therapy.⁵¹ Using specific monitoring parameters, progress is continuously monitored. Depending on the patient's health, hospital stays last an average of five days. Activity progress is objectively tracked to guarantee consistent improvement.

Phase 2, extended recovery (6 weeks–6 months), uses wearable device integration with AI-powered analysis. Multiple modalities are used in recovery optimization strategies after TKA to improve results and lower complications. Sling therapy is used to encourage active

knee flexion, and continuous passive motion is assessed for its potential to prevent joint stiffness.⁵² Structured stretching protocols are recommended to support gradual improvements in range of motion, and cryotherapy is used to relieve pain and minimize post-operative swelling.⁵² By systematically assessing knee edema, which usually peaks 3–8 days after surgery with an average 35% increase in volume and stays elevated by roughly 11% at three months, progress monitoring supports these interventions.⁵² Most patients return to almost normal daily activities within 10 months, and recovery timelines are monitored to guarantee functional improvement.⁵²

In Phase 3, long-term functional restoration is monitored through a comprehensive outcome tracking with predictive modeling. According to post-operative outcome evaluation, 88% of patients return to their pre-operative levels of physical activity and sports participation, and 70% of them continue to play sports even 10 years after surgery.⁵³ Quality of life is assessed using validated tools, and return-to-work assessments are performed according to occupation-specific protocols. Simultaneously, complication prevention strategies concentrate on lowering fall risk—TKA has been demonstrated to reduce fall risk by 54% in patients with a history of pre-operative falls⁵³—as well as tracking balance to improve mobility and offering long-term activity modification advice to support the longevity of implants.

2.3.4. Scenario 12: Technology integration and innovation

This scenario focuses on the implementation of cutting-edge technologies in TKA practice. Real-time surgical guidance is provided by computer-assisted navigation systems, which increase the precision of component placement.⁵³ Although recent research indicates improved accuracy, there have been few notable long-term results improvements.⁵³ Accurate assessment of soft-tissue tension during implant insertion is further supported by sensor-based guidance,¹ although issues with cost-effectiveness assessment and training requirements prevent widespread adoption. This technology is expanded upon by robotic-assisted surgery, which assists with soft-tissue balancing and mechanical axis.¹ Short-term results show encouraging increases in surgical precision.¹

Future directions center on integrating AI to further improve robotic system accuracy, while implementation considerations include evaluating the learning curve and validating results. Advances in materials and implant design complement these technologies, including porous-coated prostheses for stronger bonding and integration,¹ computer-assisted design and manufacturing for personalized implants, and 3D printing applications for

patient-specific prostheses.¹ Ongoing developments in material science aim to improve bearing surfaces and fixation methods, while quality assurance and validation protocols ensure the safe and effective deployment of AI-assisted surgical systems.

3. Key domains of AI implementation

3.1. Comprehensive AI system performance monitoring

A strong clinical validation framework is necessary for thorough AI system performance monitoring to guarantee safe and efficient deployment. Before being used in clinical settings, all AI systems must be thoroughly validated for diagnostic reliability.² To ensure broad applicability across healthcare settings, protocols must cover various patient populations and clinical scenarios.³ Performance monitoring includes diverse metrics, such as semi-annual tracking of patient outcomes, complication rates, and quality indicators; ongoing monitoring of system uptime, response times, and error rates; quarterly surveys assessing clinician satisfaction, usability, and workflow integration;⁴ and monthly assessments of diagnostic accuracy, sensitivity, specificity, positive predictive value, and negative predictive value, across patient populations. Validation protocols include retrospective testing on historical data to establish baseline performance, prospective clinical trials comparing AI-enhanced care to standard protocols, multi-site evaluations across institutions and populations to ensure robustness, and external validation by independent organizations to verify performance claims.⁵

3.2. Regulatory compliance and safety protocols

AI systems used in clinical practice must adhere to the Food and Drug Administration's oversight of AI-enabled medical device regulatory frameworks.⁵ It is the responsibility of healthcare institutions to determine which AI applications need regulatory clearance and to make sure that all systems in use adhere to relevant safety regulations.⁶ It is crucial to set up a thorough quality management system that includes standard operating procedures for the use, upkeep, and quality control of AI tools; required competency evaluations and staff training; incident reporting procedures for locating, recording, and fixing system errors or failures; and organized change control procedures to verify performance following system upgrades. Through ongoing performance monitoring, systematic reporting of adverse events related to AI,⁷ periodic safety reviews, and compliance with the Food and Drug Administration regulatory reporting requirements, post-market surveillance further guarantees safety and efficacy.

3.3. Ethical considerations and bias mitigation

A crucial aspect of using AI in healthcare is algorithmic fairness, which needs to be carefully assessed to avoid biases that might lead to different treatment recommendations for various patient groups.⁸ Bias detection and mitigation are crucial because ML models trained on biased datasets may unintentionally worsen already-existing healthcare disparities.⁹ The use of diverse training data that purposefully represents underrepresented populations, quarterly performance audits across demographic groups, the application of fairness metrics like individual fairness, equalized odds, and demographic parity, and ongoing real-time monitoring of AI recommendations across patient subgroups are some strategies to address these issues. Transparency and explainability are also required, with AI systems providing clear reasoning for diagnostic and treatment recommendations, documentation of how AI outputs influence clinical decisions, clear communication to patients when AI tools are used in their care,¹⁰ and maintenance of comprehensive audit trails capturing system decisions and their rationale.

3.4. Economic considerations and healthcare value

A thorough cost-benefit analysis that takes into account both initial investments and potential cost savings from improved outcomes is necessary for the healthcare economic impact assessment, which is a crucial part of implementing AI systems.¹¹ In addition to indirect benefits like workflow optimization, productivity gains, fewer complications, and improved patient satisfaction, analyses must take into consideration direct costs like technology acquisition, implementation, training, and maintenance.¹² Revenue effects from higher throughput, long-term value from lower revision rates, and litigation risk, and general improvements in patient outcomes are all included in the measurement of economic impact. Given that 718,000 knee arthroplasty hospitalizations accounted for 4.6% of all operating room procedures performed in the United States in 2011,¹³ the number of procedures increased by 93% between 2001 and 2011,¹³ and the number is expected to reach 3.48 million procedures annually by 2030,¹⁴ the economic implications of integrating AI are significant and present opportunities for both cost reduction and quality improvement.¹⁴

3.5. Healthcare system integration and scalability

To ensure that data standardization, security protocols, and workflow optimization enable AI tools to improve clinical practice rather than complicate it, a thorough AI implementation strategy necessitates careful integration with current healthcare information systems, especially EHRs.^{15,16} Assessing infrastructure capacity to satisfy present and future computational demands, implementing

thorough staff training programs catered to various user roles, and using methodical change management techniques to assist organizational transformation are all reasons for scalability. While integration with quality measurement systems allows for data-driven, evidence-based improvements in clinical practice,¹⁸ continuous quality improvement is crucial, utilizing AI capabilities to improve clinical outcomes and patient satisfaction.¹⁷

4. Discussion

4.1. Advanced multimodal AI integration: Federated learning and collaborative development

By utilizing experiences from various healthcare organizations, federated learning techniques allow AI systems to learn from various patient populations while preserving data security. This will enable models to advance without disclosing private patient data.^{19,20} A few advantages of collaborative AI development are continuous model improvement through continuous collaborative learning, privacy preservation through training without data sharing, access to larger and more varied training datasets for increased model accuracy, and distributed learning that lessens the computational load on individual institutions. Ensuring regulatory compliance with privacy and security requirements,²¹ standardizing data formats and definitions across sites, building the technical infrastructure for secure multi-institutional communication, and preserving consistent model quality across dispersed training environments are some of the implementation challenges.

4.2. Explainable AI and clinical decision support

Transparent AI implementation enhances understanding of how AI systems generate recommendations, providing clear insight into decision-making processes.²² This transparency is essential for maintaining patient trust and supporting the safe integration of AI technologies into healthcare delivery.²²

4.3. Clinical integration benefits

By making AI reasoning more understandable to doctors, transparent and explainable AI not only builds patient trust but also encourages adoption and reliance on AI-assisted care. Explainable systems also support quality assurance by enabling error detection and correction, and they offer educational value by facilitating clinical learning and knowledge transfer. Furthermore, as explainable AI satisfies regulations for medical device oversight, transparency aids in ensuring regulatory compliance.²³

4.4. Integration with emerging healthcare technologies: Precision medicine and genomic integration

AI and genomic medicine are combined in a comprehensive precision medicine framework to offer highly individualized treatment recommendations based on each patient's unique genetic profile.²⁴ Applications like pharmacogenomic analysis—which optimizes medication selection and dosage—risk prediction—which combines genetic and clinical factors for a thorough assessment—personalized therapy selection based on genetic biomarkers, and outcome prediction—which combines genetic and clinical data to improve prognostic accuracy—are all supported by AI algorithms' ability to analyze complex genomic data and predict treatment responses.²⁵

4.5. Internet of Things and smart healthcare environments

Smart healthcare environments that continuously monitor patient status and environmental factors can be created through comprehensive Internet of Things integration and AI analytics.²⁶ These systems enable the smooth transition between clinical and home-based care while supporting proactive interventions based on real-time data.²⁷ Applications include coordinated communication between care settings and providers, environmental assessment to track factors affecting recovery and health outcomes, predictive interventions through early warning systems to prevent complications, continuous monitoring through wearable technology and smart home technologies, and thorough outcome assessment with long-term monitoring.

4.6. Survivorship analysis and long-term success: Evidence-based outcome expectations

Although prostheses still pose difficulties for engineers and surgeons, current arthroplasty survivorship data show impressive success.²⁸ Long-term expectations usually range from 10 to 20 years, although results frequently surpass these estimates.³⁰ Selected implants must be nontoxic, durable, and biocompatible.²⁹ Approximately 82% of total knee replacements are expected to last 25 years, 75% reach 20 years, and 90% of artificial knees last at least 10 years, according to comprehensive survivorship statistics.³⁰ Strong functional results have been observed, with 70% of patients continuing to participate in sports even 10 years after surgery and 88% of patients returning to their pre-operative levels of physical activity.³⁰ Advanced materials and the incorporation of porous-coated prostheses for robust bonding, as well as computer-aided design and manufacturing and contemporary 3D printing techniques that enable patient-specific prostheses, are examples of technological advancements that have contributed to these results.^{31,32} Future developments center on robotic surgery for improved accuracy and outcome prediction, smart

implants with integrated sensors for ongoing monitoring, sophisticated biocompatible materials, and AI-powered customization for customized implant design and surgical planning.

5. Future directions and research opportunities

This guide has focused on integrating AI and ML into various stages of TKA for informed orthopedic clinical decision-making. Its strength lies in synthesizing current technological capabilities with clinical needs, which provides a roadmap for future innovation. However, the successful translation of these AI-driven workflows into standard clinical practice requires validation and sustained research efforts. This section outlines key areas for future investigation, emphasizing experimental validation and specific case study designs.

5.1. Experimental validation of AI-driven workflows

Future studies should focus on validating the AI-enhanced protocols suggested in this guide by proving their effectiveness and safety in actual clinical settings, going beyond theoretical frameworks. Randomized clinical trials are crucial for assessing the effects of AI-driven pre-operative risk assessments on complication rates and patient outcomes following TKA and for comparing AI-augmented clinical pathways with standard care. Long-term prospective cohort studies are also required to monitor patient outcomes five to 10 years after AI-enhanced care. Further evaluation of various AI tools can be performed through comparative effectiveness research, which analyzes how they affect resource use, length of hospital stay, complication rate, and overall healthcare value. In addition, each AI-based diagnostic tool, whether for early osteoarthritis detection, acute injury assessment, or periprosthetic joint infection diagnosis, requires independent verification of diagnostic accuracy and predictive value across diverse patient populations to ensure broad clinical effectiveness.

5.2. Broader research opportunities

Beyond specific validation, broader research is needed to ensure the responsible and effective integration of AI in orthopedics. Areas such as ethical and regulatory frameworks need to be studied to develop a robust framework and guidelines. This should also encompass data privacy and other aspects, such as regulatory pathways for AI-based equipment. Additional areas for research could include the optimization of human and AI collaboration models, where AI serves as a support tool for clinical decision-making. The scalability of this science and the long-term impact on healthcare economics and

quality of patient care need to be considered to transform orthopedic care.

6. Implementation strategies and practical considerations

Practical considerations are necessary for the effective implementation of AI-based tools in orthopedic clinical practice. Phased implementation, infrastructure requirements, data privacy, and legal compliance are key in this transformation to include AI into clinical decision-making in the hospital setting.

6.1. Phased implementation and scalability

The inclusion of AI-based tools into standard care protocols will cause a significant disruption. A phased approach, starting with a pilot program and gradually scaling up, will enable a smooth transition. The pilot program should include a small number of procedures to create a controlled environment where feedback can be gathered, which will help refine the process. Once the pilot is successful, gradually expand to other scenarios (e.g., intraoperative guidance, post-operative monitoring) and departments. This iterative process enables continuous learning and adaptation, ensuring that the framework meets the specific needs of various clinical teams.

6.2. Technical infrastructure and interoperability

The AI framework requires access to patients' data and computer processing power to process the data. Connecting to EHR systems must be secure, and robust integration needs to be developed for two-way communication. One way to implement this is through an Application Programming Interface. The AI models, particularly for image analysis (ResNet) and complex reasoning (Claude 3), require significant computational resources (e.g., graphics processing units). The hospital's information technology department must ensure the infrastructure can support the processing load without causing delays in clinical workflows.

6.3. Training and stakeholder buy-in

The changes to the procedures require new training for surgeons, residents, nurses, and physical therapists. This would incur a cost that requires buy-in from all stakeholders for additional investments. The training should be specific, stating that AI systems are decision-support tools and do not replace clinical judgment. Strong collaboration is required between the healthcare workers, information technology experts, hospital administrators, and legal and compliance officers. A dedicated multidisciplinary team should oversee the project from planning to rollout and ongoing maintenance.

7. Conclusion

This concise clinical decision-making guide demonstrates how sports medicine practitioners can systematically incorporate AI technologies into practice to encourage diagnostic accuracy, streamline treatment regimens, and improve patient outcomes across the entire spectrum of orthopedic care.³³ The evidence-based guidelines presented guide embedding AI tools that enhance clinical expertise while assuring the highest standards of patient care.³⁴

The integration of AI technologies in sports medicine is a paradigm shift toward precision medicine, and we can only expect clinical decisions to be influenced by the analysis of large data sets, predictive modeling, and evidence-based guidelines.³⁵ The 718,000 knee arthroplasty procedures alone add 4.6% to the total number of United States operating room procedures³⁵ and are projected to grow to 3.48 million procedures annually in 2030.³⁵ Evidence-based deployment of AI technologies is imperative to regulate this expanding need with enhanced outcomes.³⁶

The comprehensive protocols outlined in this guide encompass the full range of sports medicine practices, from emergency department triage to sophisticated surgery planning.³⁷ Every prototype contains specific technology recommendations, deployment methods, and expected outcomes backed by evidence and best practice.³⁸ Biomarker testing, advanced imaging, and predictive modeling enable clinicians to make more informed decisions while providing individualized treatment for each patient.³⁹

Success in AI implementation involves not merely the acceptance of technology but also systematic training, quality monitoring, and continuous improvement based on clinical performance and user feedback.⁴⁰ The quality control processes and regulatory compliance frameworks implemented ensure that AI integration is patient-safe.⁴¹ Economic analysis displays the high value of AI implementation in terms of outcome improvement.⁴²

In the near future, learning, explainable AI, and interoperability with genomic medicine will provide even greater prospects for personalized orthopedic care.⁴³ The convergence of AI with Internet of Things technologies, smart implants, and monitoring systems will create understandable healthcare environments that provide patient care.⁴⁴

Sports medicine professionals willing to embrace these evidence-based principles will be well-positioned to leverage AI technologies best, maintaining the professional judgment that defines excellent healthcare delivery.⁴⁵ The sports medicine revolution through AI integration is not only a technological innovation but rather a testament to

commitment to using the best available tools and evidence to address patient needs while maintaining the fundamental principles of medical practice.⁴⁶ The system presented is a blueprint for this transition based on current evidence and is intended to aid in the creation of technology.⁴⁷ With these stringent guidelines, sports medicine practitioners can now implement AI technologies with confidence while guaranteeing that these powerful tools complement, not replace, the clinical understanding and compassionate care that are still at the forefront of medical practice.⁴⁷

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Conflict of interest

The authors declare no conflicts of interest.

Author contributions

Conceptualization: Puja Ravi, Rahul Kumar, Kyle Sporn

Project administration: Nasif Zaman, Alireza Tavakkoli

Visualization: Nasif Zaman, Alireza Tavakkoli

Writing—original draft: Puja Ravi, Rahul Kumar, Kyle Sporn

Writing—review & editing: Puja Ravi, Rahul Kumar, Kyle Sporn

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Appendix

A1. Outline of the artificial-driven steps for the 12 scenarios

1. Comprehensive pre-operative assessment
 - Input: Patient data (demographics, medical history, lab results, imaging).
 - Step 1: Natural language processing (NLP) and data analysis: An artificial intelligence (AI) system uses NLP to parse patient notes and electronic health records (EHRs).
 - Step 2: Predictive modeling: A machine learning model analyzes structured and unstructured data to predict risk factors (e.g., infection, complications, readmission).
 - Output: A personalized risk score and a suggested, optimized treatment plan.
2. Surgical planning and prosthesis selection
 - Input: Three-dimensional (3D) computed tomography (CT) or magnetic resonance imaging (MRI) scans of the patient's knee.
 - Step 1: Image segmentation: An AI algorithm segments the bone and soft tissue from the scans to create a 3D model.
 - Step 2: Prosthesis sitting: AI simulates various implant sizes and positions on the 3D model to find the optimal fit.
 - Output: A precise surgical plan detailing implant type, size, and a guide for component placement.
3. Intraoperative decision support
 - Input: Real-time data from surgical sensors, cameras, and robotics.
 - Step 1: Real-time analysis: AI uses computer vision to analyze the surgical field, providing real-time feedback on component alignment and soft-tissue balancing.
 - Step 2: Guidance system: The system provides visual or auditory cues to the surgeon, guiding them to achieve precise bone cuts and implant positioning.
 - Output: Real-time feedback and guidance, ensuring optimal implant placement.
4. Post-operative complication monitoring
 - Input: Data from wearable sensors (e.g., smartwatches), patient-reported symptoms, and daily activity logs.
 - Step 1: Anomaly detection: An AI model analyzes the incoming data streams for deviations from a normal recovery pattern (e.g., unusual swelling, increased pain, or limited mobility).
 - Step 2: Alert system: The system flags potential complications (e.g., infection, deep vein thrombosis) and sends an alert to the clinical team.
 - Output: An early warning for potential complications, allowing for timely intervention.
5. Rehabilitation and recovery
 - Input: Video of patient exercises, sensor data from limbs, and patient-reported feedback.
 - Step 1: Biomechanics analysis: AI with computer vision and biomechanics algorithms evaluates the patient's form, range of motion, and gait.
 - Step 2: Personalized feedback: The system provides real-time, actionable feedback to the patient and adjusts the rehabilitation plan based on their progress.
 - Output: A personalized, data-driven rehabilitation plan that adapts to the patient's progress.
6. Chronic pain management
 - Input: Patient pain diaries, EHRs, and medication logs.
 - Step 1: Pattern recognition: An AI system identifies pain triggers and patterns by analyzing the input data.
 - Step 2: Predictive recommendation: The model suggests personalized interventions, such as adjusting medication dosages or recommending specific therapies.
 - Output: Optimized pain management strategies tailored to the individual patient.
7. Early osteoarthritis detection
 - Input: Molecular biomarkers from blood tests and advanced imaging (e.g., MRI) of the knee joint.
 - Step 1: Biomarker analysis: An AI algorithm analyzes the biomarker profile to detect signs of early cartilage degradation.
 - Step 2: Risk scoring: A model integrates the imaging and biomarker data to provide a risk score for developing osteoarthritis.
 - Output: An early detection report, allowing for proactive, non-surgical interventions.
8. Acute knee injury assessment
 - Input: MRI, X-ray images, and clinical notes from the emergency department.
 - Step 1: Automated diagnosis: A deep learning model analyzes imaging scans for signs of fractures, ligament tears, or other acute injuries.
 - Step 2: Report generation: An AI system automatically generates a preliminary diagnostic report for the clinician to review.

- Output: A rapid and accurate diagnosis, expediting treatment in an emergency setting.
9. Complex revision total knee arthroplasty planning
 - Input: Comprehensive patient history, past surgical reports, multiple imaging modalities, and reasons for failure.
 - Step 1: Data synthesis and analysis: A large language model synthesizes all available data to identify the root cause of the implant failure.
 - Step 2: Strategy formulation: The system suggests potential surgical strategies and their likelihood of success based on a vast database of similar cases.
 - Output: A comprehensive, data-driven surgical plan for a complex revision total knee arthroplasty.
10. Population health screening
 - Input: Large-scale public health data, including demographics, lifestyle factors, and epidemiological trends.
 - Step 1: Predictive modeling: AI identifies at-risk populations for osteoarthritis based on the input data.
 - Step 2: Resource allocation: The system suggests areas for targeted interventions, such as educational campaigns or screening programs.
 - Output: Proactive public health strategies to prevent or manage osteoarthritis on a community level.
11. Long-term implant survivorship
 - Input: Patient data from the postoperative period (activity level, weight changes) and implant-specific data.
 - Step 1: Predictive modeling: A machine learning model predicts the remaining lifespan of the implant based on patient-specific usage patterns.
 - Step 2: Proactive alert: The system alerts the clinician when the implant shows signs of wear or when a revision may be necessary in the future.
 - Output: A long-term implant survivorship report, enabling proactive management and patient education.
12. Surgical documentation and reporting
 - Input: Audio recording of the surgical procedure and postoperative clinical notes.
 - Step 1: Speech to text and NLP: An AI system transcribes the surgical audio and extracts key data points from the notes.
 - Step 2: Report generation: A large language model automatically generates a detailed, structured, and consistent surgical report.
 - Output: Automated and accurate surgical documentation, reducing administrative burden and improving consistency.