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Artificial Intelligence in Trauma and Orthopaedic Surgery: A Comprehensive Review From Diagnosis to Rehabilitation

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Abstract

Artificial intelligence (AI) has presented clinical maturity in healthcare applications. AI is reshaping orthopaedic practice by enhancing the speed and efficiency of clinical decision-making, surgical planning, and research workflows. AI enables clinicians to optimize the care pathway through rapid data processing, pattern recognition, and predictive modelling. This review examines the current AI applications across the entire spectrum of orthopaedic care and its contribution to patient care and resource utilization. Despite these promising developments, several barriers prevent widespread adoption, including concerns regarding algorithm transparency, data privacy, potential bias in training datasets, and implementation costs. The path forward requires the development of explainable AI systems that clinicians can trust and validate. As AI technology continues to evolve, success will depend on augmenting human judgment with machine precision to deliver optimal care for patients with musculoskeletal conditions.

Categories: Trauma, Healthcare Technology, Orthopedics
Keywords: artificial intelligence, computer-assisted surgery, deep learning, machine learning, orthopaedic surgery, predictive analytics, trauma surgery

Introduction And Background

Artificial intelligence (AI) has been extensively used in medicine. Trauma and orthopaedics provide a fertile ground for AI applications [1]. Globally, the burden of musculoskeletal conditions continues to rise, with trauma remaining the leading cause of disability and death [2]. Simultaneously, the ageing population in developed countries has increased the incidence of degenerative joint diseases and fragility fractures [3]. This growing demand for orthopaedic services, combined with the drive for better outcomes and greater efficiency, has accelerated the adoption of AI tools that can enhance clinical decision-making and improve the delivery of care.

The specialty's reliance on different radiological imaging interpretations for diagnosing and treating injuries has given AI a chance to shine [4]. Studies have shown promising results regarding the ability of AI to analyze and process multiple images simultaneously, providing clinicians with faster and more efficient reports that contain fewer errors than those generated by conventional methods [5]. AI applications extend to perioperative planning for open reduction internal fixation and major joint replacements [6,7]. Before surgery, AI can be used to optimize patient and surgical factors. Patient factor optimization includes risk assessment and personalized guidance to decrease postoperative complications [8]. Surgical factor optimization includes implant choice, surgical approach choice, and virtual reality simulation, which allows surgeons to experience all possible scenarios before starting the operation [9].

Today, AI encompasses numerous subfields, with machine learning (ML) being the most promising for medical research. Deep learning represents a revolutionary approach in ML that can operate independently using multiple layers of artificial neurons to process information, mimicking the structure of the human brain [10-12]. For example, when examining hip radiographs, early layers might detect simple edges, middle layers identify bone structures, and deeper layers recognize complex patterns, such as fracture lines, all without being explicitly programmed to look for [13]. Deep learning achieves this function through convolutional neural networks (CNNs), which are a specialized type of deep learning designed specifically for analyzing images, surgical videos, electronic health records, and data from wearable sensors to detect patterns that are not visible to the human eye, making them ideal for orthopaedic applications [14,15].

This narrative review aims to discuss the deep involvement of AI in many aspects of trauma and orthopaedics, as explained in Figure *1*. We highlight the importance of involving human thoughts with AI in the early stages to keep AI diversions that might occur under control.

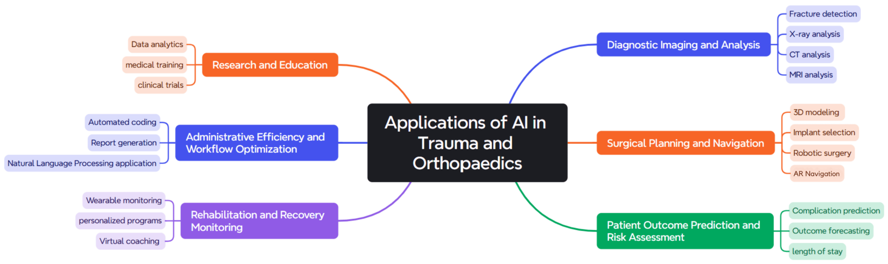

FIGURE 1: AI applications in trauma and orthopaedics

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Review

Historical evolution of AI in orthopaedics

The use of AI in orthopaedic practice has been developing for almost seven decades. The term "artificial intelligence" was introduced by John McCarthy at Dartmouth College in 1956, building on Alan Turing's earlier question of whether machines could think [16,17]. McCarthy and his team believed computers could be programmed to learn and demonstrate intelligence. However, practical applications in orthopaedics did not emerge until 1992 with the introduction of ROBODOC, the first robotic system specifically designed for orthopaedic surgery [18].

The early years of robotic orthopaedic surgery faced significant challenges. Initial systems suffered from prolonged operative times, increased blood loss, and higher infection rates [19]. The application of ML and training algorithms has helped overcome these challenges [20].

The period from 2000 to 2010 witnessed the beginning of AI invasion into healthcare domains [21]. This has occurred due to the convergence of three factors: exponential increases in computational power, widespread adoption of electronic medical records, and the development of sophisticated ML algorithms [22].

The current decade has witnessed AI achieving clinical maturity across multiple applications. Deep learning algorithms now match or exceed human performance in many diagnostic tasks, while integrated systems support the entire continuum of care [23]. The COVID-19 pandemic accelerated the adoption of AI, particularly in remote monitoring and telemedicine applications, demonstrating AI's value in maintaining care continuity during disruptions [24,25].

Diagnostic imaging and detection

Diagnostic imaging is the cornerstone of orthopaedic practice. Fracture detection represents the most mature AI application in orthopaedics [26]. In Figure *2*, we are explaining the high efficiency of AI in detecting different fracture types, achieving "88-95% accuracy as per Lindsey and colleagues [27]. The application of deep learning algorithms, particularly CNNs, has improved the ability to detect fractures and other pathological findings across all imaging modalities [28,29]. In Table *1*, we discuss the high functionality of AI-assisted ML in detecting different types of fractures.

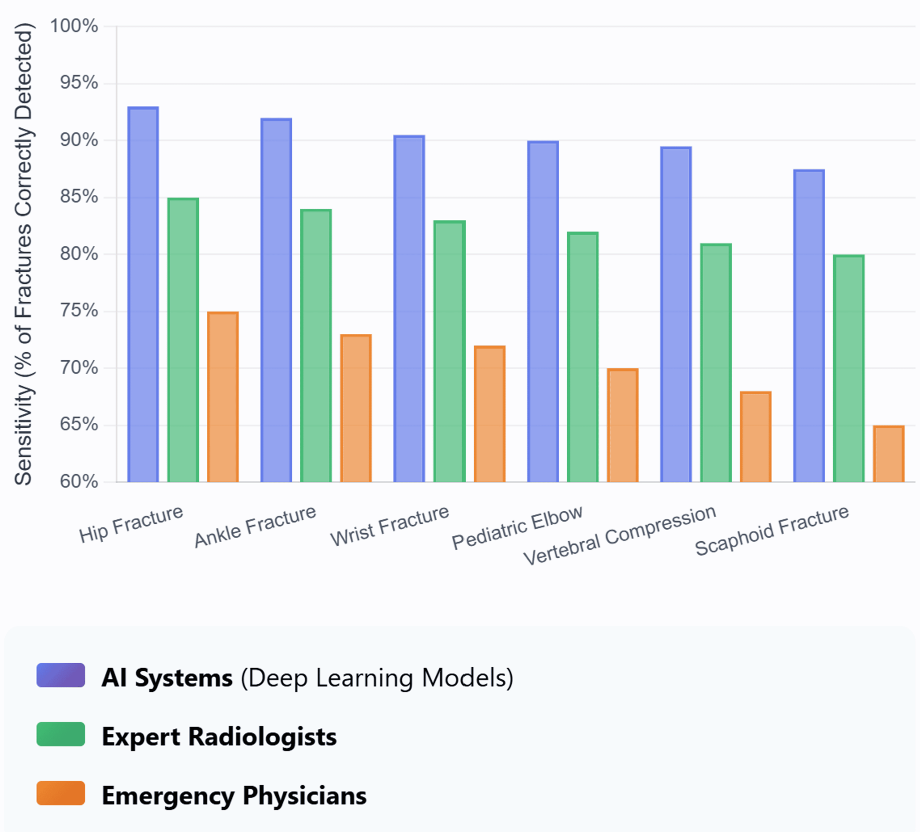

FIGURE 2: Diagnostic accuracy comparison: AI vs. human performance

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Fracture Type	Sensitivity (%)	Specificity (%)	AUC	Dataset Size	Validation Type	References
Hip Fracture	91–95	92–96	0.94–0.97	3,000–45,000	External	[30,31]
Wrist Fracture	88–93	89–94	0.91–0.95	2,500–15,000	Internal/External	[32]
Ankle Fracture	90–94	91–95	0.93–0.96	1,800–8,000	External	[33]
Vertebral Compression	87–92	88–93	0.90–0.94	2,000–12,000	Internal/External	[26]
Scaphoid Fracture	85–90	90–94	0.89–0.93	1,200–5,000	Internal	[34]
Pediatric Elbow	88–92	87–92	0.90–0.94	3,000–10,000	External	[35]

TABLE 1: Performance metrics of AI systems in common fracture detection tasks

AUC (area under the curve) refers to the overall accuracy score. The value of this metric ranges from 0 to 1. An AUC of 1 indicates a perfect value (never wrong), 0.5 indicates an unreliable value, and 0.90-0.99 indicates excellent results. Dataset size refers to the number of X-rays used to test the AI. Validation type refers to how AI was tested; internal means all data were from the same hospital, and external means data were tested from different hospitals.

The clinical impact of these systems extends beyond simple detection of abnormalities. These deep learning models can classify fractures, evaluate fracture direction and angulation, and even suggest treatment strategies [36-38]. Integration with picture archiving and communication systems (PACS) has enabled many institutions to use AI for case triage and prioritization [39,40].

The scope of AI implementation in imaging interpretation includes computed tomography (CT) and magnetic resonance imaging (MRI) analysis [41]. Deep learning models have taken this function to a high level by analyzing complex fractures in CT and suggesting virtual reduction models, providing surgeons with ideas about potential approaches to optimal fixation strategies [42]. Deep learning models have a sensitivity of approximately 87% and a specificity of 89% in detecting and marking cuts where meniscal tears and anterior cruciate ligament tears are found in MRI without human intervention, exceeding expert radiologist performance [43].

Surgical planning and navigation

The complexity of modern orthopaedic surgery demands precise preoperative planning and intraoperative performance. AI has made perioperative planning precise by generating different models. 3D modelling represents a fundamental advance in surgical planning [44]. AI algorithms create patient-specific three-dimensional models through a deep analysis of CT and MRI [6]. These models enable surgeons to visualize the targeted pathology from any angle, plan precise surgical approaches, and reduce the likelihood of unexpected intraoperative occurrences [45].

The concept of a "digital twin" has emerged as a powerful AI application [46]. This involves creating virtual and dynamic replicas of the patient's anatomy and physiology. These models enable the simulation of various surgical approaches, patients' clinical responses to interventions, prediction of potential complications, and estimation of recovery outcomes [46,47]. This gives surgeons a chance to optimize their interventions before starting the operation to ensure the best possible outcome.

Implant selection is a growing challenge in trauma and orthopaedics [48]. Different manufacturers offer different types of implants for the same fractures. Choosing the right implant requires a deep analysis of the fracture pattern, patient anatomy, biomechanics, and bone quality. AI algorithms predict implant sizes with over 85% accuracy, reducing operative time and minimizing intraoperative adjustments [9,49]. In revision surgeries, it is sometimes very difficult to identify which implant has been used from radiographs. AI algorithms identify existing implants from radiographs with over 90% accuracy across multiple manufacturers, saving valuable operative time and reducing inventory waste [50].

Robot-assisted surgery represents the convergence of AI, computer vision, and precision mechanics [51]. Modern robotic systems employ AI for real-time bone tracking, soft-tissue balancing, and dynamic plan adjustment [52]. These systems achieve precise accuracy in millimetres in bone preparation and implant positioning. The use of robots shines even more in minimally invasive procedures when visualization is limited. In spine surgery, robot-assisted pedicle screw placement shows accuracy rates exceeding 95%, compared to 85-90% with free-hand fluoroscopy-guided methods [53]. Additionally, these systems reduce radiation exposure for both patients and surgical teams by minimizing fluoroscopy requirements [54].

Augmented reality (AR) navigation systems are an emerging surgical technology. This technique uses special headsets or glasses that overlay computer-generated images, including real-time 3D images of the patient's anatomy, implant template, and measurements, directly onto the surgeon's view of the operative field [55,56]. This technology enables the surgeon to focus on important structures without diverting their attention to different monitors [57]. This "see-through" guidance acts like a GPS for surgery, improving the accuracy of implant positioning, reducing radiation exposure, and potentially shortening operative time [58,59].

Figure *3* illustrates the transformative impact of AI-assisted methods compared to traditional approaches.

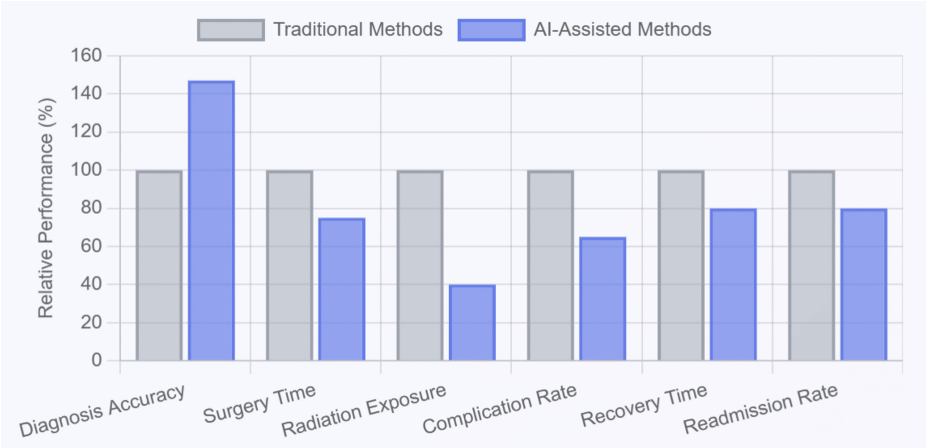

FIGURE 3: Clinical impact: AI vs. traditional methods

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Predictive analytics and risk assessment

AI has demonstrated high efficiency in predicting surgical outcomes, complication risks, and recovery trajectories [60]. ML has been trained to analyze patient-specific data, including demographics, comorbidities, laboratory values, imaging findings, and social determinants of health, to predict complications, length of stay, and forecast outcomes [61-63]. In Table 2, we examined the predictive capabilities of AI in identifying potential complications in routine orthopaedic surgeries. These predictions enable the development of proactive management strategies and appropriate resource allocation to enhance patient outcomes.

Clinical Application	Prediction Target	Model Performance (AUC)	Key Variables	Clinical Impact	References
Joint Arthroplasty	30-day readmission	0.78–0.85	Age, comorbidities, surgical time	20% reduction in readmissions	[64]
Hip Fracture	1-year mortality	0.82–0.89	Age, frailty index, albumin levels	Risk stratification for intensive intervention	[65]
Spine Surgery	Surgical site infection	0.75–0.84	BMI, diabetes, operative time	Targeted antibiotic prophylaxis	[1]
Sports Medicine	ACL re-rupture	0.77–0.83	Age, activity level, graft type	Personalized rehabilitation protocols	[66,67]
Trauma	Need for massive transfusion	0.85–0.91	Vital signs, injury severity, lab values	Early blood product preparation	[34]
Fracture Care	Nonunion risk	0.73–0.81	Fracture pattern, smoking, diabetes	Enhanced monitoring and intervention	[68]
Total Joint Arthroplasty	Periprosthetic joint infection risk	0.80–0.92	Prior infection, BMI, diabetes, operative time	Risk stratification for prophylaxis	[69]
Total Hip Arthroplasty	Hip dislocation likelihood	0.87	Postoperative radiograph features, cup angle, offset	Early identification of at-risk patients	[70]

TABLE 2: Applications of predictive AI models in trauma and orthopaedics

AUC: area under the curve; ACL: anterior cruciate ligament; BMI: body mass index

Rehabilitation and recovery

Long-term outcomes after orthopaedic surgeries are determined by postsurgical rehabilitation programs. AI has transformed the way we guide and monitor recovery through the innovative application of wearable technology, virtual assistants, and intelligent monitoring systems.

Wearable monitoring uses sensors in devices such as smartwatches, activity trackers, and smart rings to continuously assess patient progress [71]. AI algorithms convert raw sensor data into clinically relevant metrics. Smart rings can predict acute fluctuations in postoperative pain after orthopaedic surgery [72]. Ramkumar and colleagues validated an ML-based remote monitoring platform for total knee arthroplasty patients that accurately tracks recovery metrics and identifies patients requiring intervention [73].

Virtual physical therapy assistant applications represent a paradigm shift in rehabilitation delivery. They guide patients through exercises using smartphone cameras and computer vision technology for movement analysis [74]. They ensure that exercises are performed correctly, provide real-time feedback on form, and adjust protocols dynamically based on progress. Virtual assistants achieve compliance rates exceeding 80%, compared to 50-60% with traditional home exercise programs [75]. This technology is especially valuable for patients in rural areas or those with transportation limitations. Moreover, they decrease the pressure on physiotherapists. During the COVID-19 pandemic, these systems proved essential for maintaining care continuity when in-person therapy was unavailable [76].

Administrative and documentation

Administrative jobs are a burden on healthcare providers. They consume valuable time that could be spent on patients. AI offers powerful solutions to streamline these essential but time-consuming tasks, improving efficiency while maintaining quality and compliance with regulations.

Automated coding uses natural language processing (NLP) to extract procedure codes and complications from operative notes and clinical documentation, with accuracy rates exceeding 90% [77,78]. This automation allows coding professionals to focus on complex cases requiring human expertise, while routine cases are processed automatically. This technology has reduced coding time by up to 50% while improving accuracy [79].

Report generation is a significant challenge, especially on busy clinical days. Large language models can generate discharge summaries, operative reports, and clinic notes in seconds rather than minutes or hours while maintaining the same quality as clinicians' reports [80]. Recent pilot studies have demonstrated that GPT-4 generates discharge summaries while reducing documentation time by 40% [81,82]. NLP is particularly important in the clinical setting. Physicians can dictate notes while AI structures the information appropriately through voice-to-text transformation with error rates below 2% for medical vocabulary [79].

Research and education

AI accelerates scientific discovery and enhances medical education in orthopaedics through innovative applications that transform research, training of future surgeons, and clinical data analysis.

The importance of AI in medical research begins with study selection and design [83]. ML algorithms can identify eligible patients and sample sizes through a deep analysis of health records and databases, increasing enrollment rates by up to 30% [84,85]. Moreover, recent AI models can predict patients who will most likely complete the trials, helping researchers optimize recruitment strategies and reduce dropout rates [86].

When it comes to writing and publishing, AI tools can perform full statistical analyses, generate tables and graphs, and suggest subheadings that the researcher can build the whole article on [87]. AI-powered applications can transform individual thoughts and simplify, paraphrase, or convert them into academic writing. This function is particularly valuable for non-English speakers who struggle with academic writing [88].

Medical training has been revolutionized by AI-powered simulators and educational tools. Virtual reality and simulation systems help trainees practice procedures in risk-free environments with unlimited repetitions [89]. AI provides personalized feedback based on performance, identifies areas needing improvement, and creates personalized training plans based on individual skill levels [90].

Challenges and limitations

Despite remarkable advances, significant challenges limit AI's full potential of AI in orthopaedics. Understanding these limitations is crucial for their successful implementation and continued development.

Ethical concerns regarding data security are a fundamental challenge in relying on AI. AI systems are trained using large amounts of patient data. The way these data were handled later is questionable [91]. Bias regarding the algorithms used to train AI is another challenge. Datasets used to train AI are often not diverse and represent only a single institution or a small group of people, which poses a challenge to the generalizability of these data outcomes [92]. The AI algorithms themselves are considered a "black box." Healthcare systems may be reluctant to employ AI systems whose decision-making processes cannot be clearly explained. Error analysis and system improvement in black box algorithms when failure occurs can be impossible, making their reliability poor [93].

Substituting traditional and well-established healthcare systems with new AI systems is another challenge. This will require hardware tools, software licensing, staff training, and workflow redesign, which can be prohibitive for smaller institutions or those in resource-limited settings [94].

Future directions

The effect of AI on trauma and orthopaedics is promising and will likely shape the field in the coming years. Federated learning (FL) is emerging as a solution to data privacy concerns. Instead of data centralization, FL allows data to be stored only on the user's device, which keeps the data local and maintains privacy [95].

The integration of multiple AI modalities into comprehensive clinical decision-making is revolutionary. Future systems will combine imaging analysis, outcome prediction, surgical planning, and rehabilitation monitoring into a unified platform supporting the entire continuum of care [96]. These integrated systems will provide consistent, evidence-based recommendations throughout the patient's journey.

Although quantum computing is still in its early stages, it has the potential to dramatically accelerate certain

AI tasks. These new systems can analyze data and optimize surgical planning through unparalleled approaches that go beyond the scope of traditional computers [97].

The introduction of explainable AI makes it more transparent and trustworthy. New techniques that can visualize and explain the way of thinking and decision-making have been introduced to the market. This allows clinicians to detect any errors and redirect the systems to solve them, facilitating appropriate clinical integration [98]. Educational programs should be introduced to prepare surgeons to effectively utilize these tools while maintaining critical thinking when AI recommendations conflict with clinical judgment.

Conclusions

The integration of AI into trauma and orthopaedic practice represents a paradigm shift in the diagnosis, treatment, and management of musculoskeletal conditions. AI systems are guiding the patient management journey from diagnosis to personalized rehabilitation protocols. Success requires collaborative efforts involving clinicians, data scientists, and policymakers to overcome the current challenges. The development of robust validation frameworks, standardized performance metrics, and transparent reporting guidelines is essential for building trust and ensuring safe deployment.

Looking forward, the future of trauma and orthopaedics will be characterized by seamless integration of AI technologies throughout the entire care pathway. The key to successful integration lies in maintaining a patient-centred approach, ensuring equitable access to these technologies, and preserving the essential human elements of compassion, creativity, and clinical wisdom that define excellent medical care. As we advance into this new era, research, continuous monitoring, and careful attention to ethical considerations will be crucial as AI becomes more involved in the field. The goal is not to replace human expertise but to augment it, creating a synergy between human judgment and machine precision that delivers high levels of care to all patients.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

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Drafting of the manuscript: Ahmed Mohamed, Alaa Elasad, Ioannis Pengas, Prabhakar Bhamidipati, Peter Salib

Critical review of the manuscript for important intellectual content: Ahmed Mohamed, Usman Fuad, Adham Elsayed

Supervision: Ahmed Mohamed

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