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Current Concepts Review

Artificial intelligence and the orthopaedic surgeon: A review of the literature and potential applications for future practice: Current concepts

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Current Concepts

- Artificial Intelligence in medicine (AIM) and surgery (AIS) should be considered as two related but distinct entities. The combined use of AI and deep learning along with human interpretation for automated measurements in orthopaedics yields excellent results.
- AI has been used successfully to facilitate decision making when it comes to prognostication. These models still require human oversight due to the complex nature and variables involved.
- Robotic-assisted arthroplasty improves implant positioning in both hip and knee arthroplasty, there is less conclusive evidence to support improvement in functional outcomes or long-term survival of these implants.
- Simulation technology is on the rise and is has been increasingly used as an adjunct to traditional models. These models cannot be used as a substitute to traditional training.

Future Perspectives

- Abstract concepts such as intuition which are difficult to impart to a machine in the form of computer code remain elusive and further work is needed to refine these processes to a point where human oversight is minimal or redundant.
- AI driven prognostication models remain in their infancy. More work is needed to guide treatment pathways and formulate strategies to guide preventative medicine.
- Whilst robotic assisted surgery and Virtual reality has improved surgery in numerous domains, this has not yet translated to an improvement in patient outcomes. Until these are achieved, further development may be required into the optimisation of these technologies.

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INTRODUCTION

Over the last two decades, the application of Artificial Intelligence (AI) to the field of surgery has developed exponentially, with the number of PubMed search results for "artificial intelligence" more than doubling between 2019 and 2021, according to Chen et al. [1]. The surge of interest in the orthopaedic applications for AI is also noticeable [2]. The number of total publications and citations whose title, abstract, and/or keywords refer to the field of AI in orthopaedics has grown by a factor of ten between 2017 and 2021 [3]. Improvements in computer science, processor speeds, and associated technologies have seen AI drive increasing applications relevant to orthopaedic field [3]. Advances in muskuloskeletal imaging [4], arthroplasty planning [5], robotics, and computer navigated surgery [6] have proved to be useful tools in the orthopaedic armarium. The rapid rise in the application of these technologies has not always been followed by an uptake in use, with many remaining reluctant to engage with the technological tools available fully. The causes for this phenomenon remain complex and multifactorial. The associated cost, required retraining, and lack of thorough education on the benefits of AI may all contribute in part to this slow uptake of use. This current concepts review aims to synthesise the available literature on the subject, facilitating the understanding of this complex field and its application, relevance, and usefulness to the orthopaedic surgeons.

To facilitate the reader's understanding of the literature, we have broken down the subject matter into 5 broad categories:

- Diagnostics and enhanced decision support.
- Predictive analytics.
- Robotics and its use in surgical planning and augmentation.
- Rehabilitation.
- Teaching and training (including virtual reality [VR]).

This allows the reader to understand the impact of AI on the whole of the patient care pathway. This starts at the level of diagnosis and imaging of pathology, follows through to prognostication and prediction models. The preoperative planning phase is covered as well as the impact of AI technology on the operative process itself. Finally, the postoperative management of patients (with an emphasis on bespoke rehabilitation and telerehabilitation) is covered, with a final emphasis on the use of AI in surgical training.

KEY DEFINITIONS

When examining the literature regarding AI, it is clear that multiple terms are often used interchangeably. This in itself may be confusing; it is essential to understand and define these terms clearly.

John McCarthy coined AI as a theory that computers could eventually learn to perform tasks through pattern recognition and with minimal to no human involvement [7]. AI is the theory and development of computer systems able to perform tasks normally requiring human intelligence.

The application of AI to medicine and surgery should be considered as two related but distinct entities [8], with the former being used to manage or treat patients without a specific interventional procedure as the intended result of prognostic or diagnostic investigation.

The terms AI, machine learning (ML), and deep learning (DL) are often used interchangeably [4]; however, there are differences in the meaning of each term.

Whereas AI refers to technology that enables computers to mimic human intelligence, ML is a subset of AI that allows machines to improve their performance by developing experience with the help of statistical and mathematical tools. ML algorithms can learn from examples to enhance the accuracy of synthesised predicted models. ML algorithms can also be trained in a supervised or unsupervised manner. An example of supervised learning is predictive modelling. This is a statistical technique to predict future behaviour. Predictive modelling solutions are a form of data-mining technology that analyses historical and current data in order to generate models, which in turn help predict future outcomes. An example of unsupervised learning is cluster analysis which involves applying clustering algorithms with the goal of finding hidden patterns or groupings in a data set.

DL is essentially a more refined subtype of ML that studies computational models (deep neural networks) exposed to large datasets [4]. DL is capable of unsupervised learning from unstructured data, filtering out data input from variables of low relevance to a prediction of interest.

The applications of AI in surgery are potentially limitless, and an in-depth investigation into all of these is beyond the scope of this article. For ease of understanding, we have chosen to cover several key topics most relevant to the modern orthopaedic surgeons. These are medical imaging, prognostication, robotics in surgery, and rehabilitation as well as VR and simulation.

DIAGNOSTICS AND ENHANCED DECISION SUPPORT

The assignment of AI-guided tasks was met with initial success. Computer programs easily mastered complex calculations and mathematical predictions that were difficult for humans to perform, particularly with the advent of advanced computer processors. Paradoxically, simpler tasks—such as image or object recognition [1]—were more difficult for AI to master as they involved abstract concepts such as intuition which are difficult to impart to a machine in the form of computer code.

Nevertheless, AI has revolutionised each stage of the imaging pathway, with improvements in imaging acquisition, interpretation, reconstruction, and analysis [9]. Incorporating patient records, clinical findings, and laboratory results has led to improved patient algorithms capable of optimising patient-specific and appropriate imaging protocols. AI has also improved the speed of imaging acquisition. This is particularly relevant to imaging modalities such as magnetic resonance imaging (MRI) [10]. Investigations that are reliant on ionising radiation have also benefitted, with the overall dose associated with scans being reduced by AI optimisation [11].

Plain radiographs

The application of AI to radiograph interpretation still requires improvement. Most plain radiographs are reported by healthcare professionals with narrative descriptions of the images being assessed. The potential for AI to relieve some of the burden of routine image interpretation may in time reduce the burden of workload, eliminating the risk of stress-induced interpreter error, which has been reported to be as high as 40% [1]. Inter- and intra-observer variability and the learning curve associated with image reporting is also a problem in radiograph interpretation. Examples of this phenomenon can be seen in the measurement of acetabular component positioning—with DL measurement tools being developed to facilitate this process [12].

AI-assisted estimation of bone age is more effective than diagnosis by a radiologist operating alone—though the best results can be achieved with the refinement of the technique with human assistance [13].

The use of AI and DL in interpreting automated measurements (leg alignment, joint orientation and leg length) is of equal accuracy but more time-effective than with human eyes alone [1]. It is important to note that in these studies, severe deformities and poor image quality were exclusion criteria and that human supervision remains an essential component of using these techniques.

The use of ML and DL has excellent potential for application to fracture detection. The recognition of common fracture patterns can be imparted algorithmically to AI. Several studies have compared DL algorithms to human performance when recognising fracture patterns [14].

The accuracy of fracture detection was high. The sensitivity and specificity of hip fracture detection are as high as 97.1 % and 96.7 %, respectively [15]. In fracture localisation, performance was lower, ranging from 95.8 to 20% depending on fracture location.

Liu et al. compared the performance of orthopaedic surgeons with AI at detecting tibial plateau fractures [16]. The accuracy of the recognition algorithm was found to be comparable to human performance. However, the main benefit was found to be in speed, with AI found to be 16 times faster than orthopaedic surgeons.

There may be a role for AI in the detection of more specialised fractures, which are difficult for the generalist orthopaedic surgeon to detect, such as vertebral fractures. The rate of missed vertebral fractures can be as high as 30 % on plain films [17]. Deep convolutional neural networks designed to detect vertebral fractures are as accurate as orthopaedic surgeons in detecting vertebral fractures. However, these were less accurate than spine specialists [18], indicating room for improvement in this field.

Other body areas studied include the wrist, femur, hand, and proximal humerus [14]. In general, the accuracy of fracture detection is high, ranging from 83 to 98%. With fracture classification, the accuracy ranges from 70 to 90% in the limited studies available [14]. Some studies have assessed the use of AI in measuring the curvature of the spine in scoliosis [19,20]. AI has subsequently been used to detect disc herniation [21].

Advanced imaging

Studies have been performed on both MRI and computed tomography, particularly in the setting of trauma [22]. The accuracy and speed of detecting rib fractures are more accurate when radiologists employ the assistance of a DL model. The use of AI-assisted diagnostics with MRI has facilitated the detection of injuries to the anterior cruciate ligament (ACL), Menisci and cartilage within the knee [1], with a systematic review by Siouras et al. [23] suggesting that the use of AI in MRI has the potential to be on par with human-level performance, showing a prediction accuracy of 72.5–100%.

Overall, limited studies show that AI performance is comparable to human interpreters. These studies are limited for several reasons, notably their design. They are often based on one image projection. In reality, the patient studied will have multiple views available, combined with a history and clinical examination. All standards of pattern recognition within these studies are set by human standards and, therefore, subject to human error. Finally, the overall number of these studies could be higher and of better quality. This fact, combined with the potential for publication bias, means that the potential for the use of AI may currently be overplayed. A greater number of higher quality studies is needed.

PREDICTIVE ANALYTICS

AI can be used to facilitate decision-making with the recognition of complex results of analyses such as risk predictions, prognostications, and treatment algorithms. This can guide the patient's pathway within an appropriate clinical context [24], though ultimately the treating surgeon and patient must interpret any data and use it to guide a shared decision-making process. This decision-making process can predict the clinical outcome of patients based on clinical datasets, genomic information, and medical images. Kim et al. were able to use ML to predict the complication rate of adults undergoing spinal deformity corrective surgery [25].

ML has been used to predict minimal clinically important differences in patient-reported outcomes following osteochondral graft transplantation in knee surgery [26]. This process has also been applied to decision-making regarding surgical outcomes and expectations in hip arthroscopy [27], the progression of knee arthritis [28] leading to arthroplasty, the need for hospital admission following ACL surgery [29], or the need for prolonged postoperative analgesic use following arthroscopy [30].

Clinical decision support systems have also been used to provide recommendations on the diagnosis and treatment of lower back pain [31], with Hill et al. designing a screening tool which identified at-risk subgroups of patients and guided the provision of early secondary prevention in primary care. AI may, therefore, be useful in efficiently allocating services and improving referral pathways. These pathways must factor in a number of variables, including age, gender, comorbidities, and ethnicity.

ROBOTICS AND ITS USE IN SURGICAL PLANNING AND AUGMENTATION

The advent of the robot and its application to the field of orthopaedics has developed rapidly over the last two decades. Robotic surgery utilises the advantages of complex computer calculations to optimise surgical performance, be it in the implantation of prostheses or implants, fracture reduction, or in the rehabilitation of orthopaedic patients.

The rationale behind robotically augmented surgery lies in the basis that the knowledge and experience of correct prosthetic implantation lie ultimately with the surgeon. The ability to apply this skill consistently and accurately may be deficient due to human error. Several generations of robotically assisted tools have been developed to improve consistency among arthroplasty surgeons to improve implant position and alignment and, ultimately, patient outcomes (function and implant survival). Computer programming and planning of implant position all revolve around the accurate imaging of affected body parts, consideration of limb alignment, and soft tissue tension. This, in turn, should theoretically translate to correct bony preparation, precise cuts, and restoration of the physiological function of the limb. Inaccuracy of this process inevitably leads to implant malposition and, ultimately, failure [32].

Robotic systems may be known as “Closed” or “Open”. The former is compatible only with the type of implant associated with the robot's manufacturer. The latter allows for a broader range of implants. It is ultimately up to the surgeon to weigh the pros and cons of each type of robot and whether the features of an individual model outweigh the restrictions of its use and the subsequent impact on surgical freedom.

Robotic systems may be image-based or imageless, with the former system reliant on the preoperative visualisation of a patient's anatomy and key mapping points used as reference points for device implantation [33]. Preoperative imaging (CT or MRI) is crucial to this process. The image-based approach allows for better preoperative preparation. Still, it comes with the disadvantages of increased cost, radiation exposure (in the case of CT), and reliance on imaging which must be taken close to the time of surgery.

With imageless surgery, the detection and registration of the required landmarks and surfaces directly on the patient's bones occur after exposure intraoperatively. The advantages of this approach are the lower cost, avoidance of preoperative radiation, and temporal flexibility of operative intervention. These must be weighed against the disadvantages of 1. less flexibility in the application of orthopaedic condition, of which all the landmarks have to be constant e.g. arthroplasty but not fractures and 2. more insufficient preparation, which may impede a surgeon's ability to preselect appropriate implants and ensure their availability, particularly in more complicated surgeries where the anatomy may require patient-specific or rare implants.

Robotic systems may be known as active, passive, or semi-active. Active robotic systems are pre-programmed by the surgeon, but after registration, the level of human interaction is the lowest as the robot performs autonomously [33]. Passive robots work oppositely, with the robot merely guiding the surgical process, with the surgeon mainly in control of the resection, with the robot providing a positioning guide based on pre-planning. Some systems allow for the measurement of soft tissue tension intraoperatively, permitting further verification of the performed bony resection [34].

Semi-active systems follow a hybrid approach between the aforementioned surgical techniques, allowing for surgical planning followed by surgeon-controlled resection. This resection is augmented by haptic feedback and safety measures limiting deviation from the defined surgical plan. The robot will regulate certain aspects of the resection, but these features may be overridden by the surgeon, who remains in ultimate control [33].

Robotics in arthroplasty

Most advances in robotics have occurred in lower limb arthroplasty, representing over 90% of the implant market [33].

While it has been well established that robotic-assisted arthroplasty has been proven to improve implant positioning in both hip and knee arthroplasty, there is less conclusive evidence to support improvement in functional outcomes or long-term survival of these implants [35,36]. An economic analysis by Pierce et al. [37] revealed that robotic-assisted surgery was associated with shorter length of stay, reduced utilisation of services, and reduced 90-day costs compared with non-robotic-assisted surgery. From a technical perspective, robotic-guided surgery has been found to reduce the learning curve in the implantation of unicompartmental knee arthroplasty [38,39]. One must consider that authors associated with the studies mentioned carry conflicts of interest. Further evidence is needed with more research into the long-term outcomes of robotic-assisted arthroplasty.

Robotics in spinal surgery

The most common focus of robotic surgery in spinal orthopaedics is the use of computers to guide the placement of pedicle screws [40]. Freehand placement techniques have been historically used but are associated with component misplacement and subsequent complications, including neurological and vascular complications. Further advances in the field will focus more on more complex fusion procedures such as higher cervical fusions and S2-sacral-iliac screw placement [40].

The most extensively studied robotic spinal systems revolve around several key steps [41]. The first is preoperative planning, where CT imaging is uploaded to pre-programmed software, and the optimal implant trajectory is calculated. A small robot is then mounted on the spine. Three-dimensional syncing occurs whereby the preoperative imaging is matched to the patient's anatomy via intraoperative fluoroscopic imaging. Finally, a robotic arm is used to guide the trajectory of instrumentation.

Future innovation in this field will revolve around augmented reality as well as machine-guided image surgery which allows the operator to perform surgery without the associated risk of radiation and will help address line of sight issues which may hamper instrument tracking [40].

Robotics in trauma

Most of the existing literature concerning the use of robotics in orthopaedics involves robotically assisted elective procedures, as most of these procedures have standardized technique and landmarks. Nevertheless, some studies have been performed on trauma patients. A recently published systematic review [42] outlining the key benefits of robotic-assisted fracture reduction has been used in several settings. The review focused on the following parameters: planning time, operating time, fluoroscopy time/frequency, screw placement accuracy, intraoperative blood loss, postoperative physical performance/functional outcomes and wound/fracture healing time.

Overall, a robotic intervention was found to have a net positive impact on trauma surgery, with reduced operating [43]/fluoroscopy times [44] and fluoroscopy frequency [44]. Improvements in screw placement accuracy were reported in the fixation of pelvic fractures [45]. Although intraoperative blood loss was reduced, no current consensus exists on the definition of a clinically relevant volume. The Standardised Endpoints for Perioperative Medicine collaborative is currently conducting a review to reach a consensus on this matter [46]. Postoperative physical performance and functional outcomes were not enhanced in the studies performed, and fracture healing times were unaffected.

Overall, the available quality of evidence reviewed was considered low, with a high risk of bias. It is difficult to find any directly tangible benefits to the patient with the available body of evidence, especially considering the increased cost of robotic surgical equipment. More work is needed to justify the use of robotics more firmly in the future.

Robotics in rehabilitation

Robotic and sensor-based neurologic rehabilitation programmes are well established and recommended for upper [47] and lower [48] limb rehabilitation. The importance of rehabilitation following trauma or elective procedures is proven, and the increasing paucity of available rehabilitation resources may mean that clinicians should prove innovative to cope with an increasing clinical burden.

Robotic treatment of the lower extremity focuses primarily on promoting prescribed gait patterns

The treatment of upper limb injuries remains much more complex. This is partly due to the complexity of upper limb movement (there are 27 degrees of freedom in the upper limb). Both the variety and complexity of tasks required by the upper limb further complicate the rehabilitative process. It has been mainly used in the training for preparation of the myeloelectric prosthesis for upper limb amputees. This enables patients to perform more intuitive movements when their prosthesis are available and in turn encourage compliance of the use of prosthesis. In a recent pioneering study [47], Jakob et al. designed a matrix-like approach to treating upper limb injuries using integrated robotic and sensor-based devices to address distal and proximal training. Patients were stratified by level of disability.

In a multicentre randomised controlled trial, robotic group therapy was found to reduce costs by 50% with equivalent outcomes.

Much work remains to be done—and it should be noted that the initial equipment and training costs may be high. However, any initial expense or investment may eventually be offset by savings accrued by the long-term economic benefits of computer-assisted rehabilitation without adversely affecting patient outcomes.

REHABILITATION

There are further uses for AI in orthopaedic rehabilitation that extend beyond robotics. Wearable technology offers a source of rich, epidemiological data through surveillance of physical behaviour [49]. Smart wearables employ AI to monitor behaviour, activity recognition, and pattern recognition. This allows treating physician or physiotherapist to monitor exercise adherence and accuracy, which can often be poor. Burns et al. [50] tested performance accuracy on individuals who performed a rotator-cuff exercise protocol whilst wearing an Apple Watch. Various methods of supervised learning were used to classify exercise accuracy. Simple interventions such as these which are easily adapted by patients are promising, though further research on such techniques is warranted as they are relatively novel.

Though the topic of augmented reality will be covered in more detail further on, its use in the process of patient rehabilitation has increased in recent years, with the development of technologies such as the Cave Automatic Virtual Environment. This system consists in a square room typically composed by either 4 or 6 six back projected screens which are combined with glasses for 3D vision. This in turn provides a continuous projection surface. A linked head-tracking device allows display of real-time images according to the participant's point of view, while the audio stimuli are delivered by speakers positioned around the device [51]. Such devices are not only useful in helping create a controlled environment where patient rehabilitation can be tested but they may also allow rehabilitators to assess patient confidence and slowly build it up in a measured, observable manner without subjecting the patient to undue risk out in the community.

Widespread advances in telecommunication technology have increased our ability to deliver rehabilitation via the internet (i.e. telerehabilitation). The use of such technology in conjunction with the aforementioned VR and wearable technologies will no doubt broaden the access of patients to rehabilitation, particularly when they are located in remote areas which are poorly served by local healthcare services. This in turn may ensure improved continuity of care as well as patients monitoring and postoperative counselling [52]. Several studies have shown that telerehabilitation is effective to improve clinical outcomes in disabling conditions [52]. In a systematic review of the literature conducted by Agostini et al. [52], a strong positive effect was found for patients following orthopaedic surgery, suggesting that the increased intensity provided by telerehabilitation holds promise as a method of rehabilitation.

SIMULATION, TEACHING, AND TRAINING IN ORTHOPAEDICS

The traditional orthopaedic approach to training has been one of apprenticeship, whereby orthopaedic trainees are slowly guided towards a more complex skill set based on operating time spent effectively practising on patients under supervision. This training model bears significant drawbacks regarding time efficiency and patient safety and relies on the goodwill of surgical trainers within the context of adequate service provision.

The concept of virtual surgical training has evolved to bypass some of these obstacles. The aim is a more efficient surgical training model, making optimal use of available technological resources to improve a surgeon's skillset with maximal training opportunities at a minimal cost to the patient. The first surgical simulators can be traced back to the early nineties [53]. However, the relatively primitive technology resulted in a reluctance to adopt technology as a surgical training tool.

With the advent of more modern simulation technology, research has focused on adapting technology to allow surgeons to develop skills in several fields, from procedural (arthroscopic/arthroplasty) to sensory (haptic feedback technology).

The application of AI technology to simulators enhances the training experience by providing personalised feedback to the user, while also automating an immersive surgical experience for visualisation of patient anatomy [54]. AI is able to enhance surgical training simulators by evaluating a subject's performance and providing individualised feedback to the end user [55].

The value of retention of surgical skills gained in simulation has been demonstrated at six months post training [56], though this finding is contradicted in other parts of the literature [57]. It is important to note that studies on the subject of retention are rare and usually involve different procedures, so drawing any firm conclusions on the matter is complex. Simulators fail to simulate the stressful conditions present in emergency surgery. However, one could argue that the purpose of the surgical simulation is to develop motor skills that are second nature, to be deployed unconsciously in times of stress. In addition, it helps surgeons to maintain the skills e.g. in the time of COVID – 19 where there is a lack of cases.

For surgical simulators to be used successfully, they should be deployed within a predetermined training framework containing several key steps. These begin with a sound theoretical understanding of the techniques used, followed by simple simulators and more complex tasks. These are followed by a cadaveric test run before the surgeon in training can operate on human patients. While this model is sound in theory, the realities of the associated costs mean that such a model is likely to see an uptake in general surgical use once the resources to do so become widely and more cheaply available.

The future of arthroscopic simulators lies in the employment of haptic feedback devices, though these are only widely available. Current active haptic technology, which employs motors to simulate tactile feedback, does not demonstrate sufficient face validity or match the sophistication of passive haptic systems in high-fidelity arthroscopy simulators.

VR IN SIMULATION

VR technology has come a long way in its application over the last two decades. Initial application from its use in aerospace technology has translated to use in multiple professional and recreational fields, including engineering, gaming, military technology, and medical science. The technology in question has been used for prosthetic sizing/placement, remote surgery, phantom limb pain therapy, physical therapy, joint injection as well as mobile app-based education [58].

The use of VR models can not only be employed in surgical training but also within the operating theatre itself, with the ultimate aim being aims to increase operative accuracy and improve safety by decreasing procedure-related complications [58].

AI can be used in conjunction with VR to enhance the personalization and adaptation of VR interventions. AI can also improve the interactivity and realism of VR experiences by enabling natural language processing, computer vision, and ML capabilities [59].

VR can be broken down into 3 subcategories [58].

1) Full visual immersion: This is in an artificial, computer-generated environment. Artificial sounds and other stimuli may also be generated. This can be used in preoperative planning, patient education, and surgical training.
2) Augmented reality: A digital display overlay on real-world surfaces, which allows for depth perception. This may be used in preoperative planning, intraoperative guidance, and training
3) Mixed reality: This technology uses a digital display overlay combined with interactive projected holograms. The surgeon views the real world while manipulating digital content generated by the device using commands and hand gestures. This may be used in preoperative planning, intraoperatively for guidance and in training.

The theory is that visual and retinal displays worn on a surgeon's face in the form of goggles or glasses may relay information to the operator in real-time—displaying both geometric guidance and the accuracy of instrument placement. Such technology has excellent synergy with other technological advances, including robotic surgery, and the two techniques are increasingly used in conjunction with one another.

Retinal displays and the use of mixed reality may also be used to view 3D representations of preoperative imaging, allowing surgeons to better orientate themselves according to the patient's native anatomy.

There is level I evidence supporting the use of VR in surgical training with increased procedural accuracy and the completion of tasks demonstrated in medical students using the technology compared to those using guides [60]. VR is thought to augment learning the procedural workflow and movements required to perform surgical tasks.

A recent study comparing VR arthroscopic simulation [61] with cadaveric models demonstrated superiority in task completion time. There is scant evidence in the literature comparing the two training techniques. The benefits of simulated surgery lie primarily in cost savings compared to the expense and sparsity of cadaveric training models.

A potential benefit of augmented reality that has yet to be fully explored is the potential reduction in radiation exposure to the patient and operating theatre staff, with sensors being able to direct the surgeon to place metalwork without the need for potentially harmful X-rays [62].

Although the initial costs associated with the use of VR technology may seem prohibitive, surgeons considering its use should consider the fact that these costs may be offset by the gains improved performance, training and ultimately the patient.

CONCLUSIONS

The field of AI in orthopaedics is exponentially growing. It enhances surgeons' performance in many different areas, including diagnosis, and precision of surgery. This in turn aims to improve the outcome of patients care. The ability of surgeons to keep pace with this rapidly evolving field will be vital to exploiting future technological developments. Future accessibility and education remain key to the achievement of this goal. A significant volume of research contained within the engineering literature may not be readily accessible to orthopaedic surgeons and may not reach readers with a clinical background [63]. Future integration of AI, robotic, and VR-related education is the solution. Changes must be implemented to medical and surgical curricula at an early stage in order to ensure a future optimised for the highest quality of patient care.

Declaration of competing interest

All authors declare that they have no conflicts of interest.

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