JSES Reviews, Reports, and Techniques 3 (2023) 447–453

Contents lists available at ScienceDirect

JSES Reviews, Reports, and Techniques

journal homepage: www.jsesreviewsreportstech.org

Current clinical applications of artificial intelligence in shoulder surgery: what the busy shoulder surgeon needs to know and what's coming next

Rodrigo de Marinis, MD[a,b,c], Erick M. Marigi, MD[a], Yousif Atwan, MD, MSc[a], Linjun Yang, PhD[d], Jacob F. Oeding, MS[a], Puneet Gupta, BS[e], Ayoosh Pareek, MD[f], Joaquin Sanchez-Sotelo, MD, PhD[a], John W. Sperling, MD, MBA[a,*]

[a]*Department of Orthopedic Surgery, Mayo Clinic, Rochester, MN, USA*
[b]*Department of Orthopedic Surgery, Pontificia Universidad Católica de Chile, Santiago, Chile*
[c]*Shoulder and Elbow Unit, Hospital Dr. Sótero del Rio, Santiago, Chile*
[d]*Orthopedic Surgery Artificial Intelligence Lab (OSAIL), Mayo Clinic, Rochester, MN, USA*
[e]*Department of Orthopaedic Surgery, George Washington University School of Medicine and Health Sciences, Washington, DC, USA*
[f]*Department of Orthopaedic Surgery, Hospital for Special Surgery, New York, NY, USA*

A R T I C L E I N F O

Keywords:
Artificial intelligence
Machine learning
Deep learning
Shoulder surgery
Decision-making
Computer vision
Preoperative planning
Shoulder

Level of evidence: Level V; Review Article

Background: Artificial intelligence (AI) is a continuously expanding field with the potential to transform a variety of industries—including health care—by providing automation, efficiency, precision, accuracy, and decision-making support for simple and complex tasks. Basic knowledge of the key features as well as limitations of AI is paramount to understand current developments in this field and to successfully apply them to shoulder surgery. The purpose of the present review is to provide an overview of AI within orthopedics and shoulder surgery exploring current and forthcoming AI applications.
Methods: PubMed and Scopus databases were searched to provide a narrative review of the most relevant literature on AI applications in shoulder surgery.
Results: Despite the enormous clinical and research potential of AI, orthopedic surgery has been a relatively late adopter of AI technologies. Image evaluation, surgical planning, aiding decision-making, and facilitating patient evaluations over time are some of the current areas of development with enormous opportunities to improve surgical practice, research, and education. Furthermore, the advancement of AI-driven strategies has the potential to create a more efficient medical system that may reduce the overall cost of delivering and implementing quality health care for patients with shoulder pathology.
Conclusion: AI is an expanding field with the potential for broad clinical and research applications in orthopedic surgery. Many challenges still need to be addressed to fully leverage the potential of AI to clinical practice and research such as privacy issues, data ownership, and external validation of the proposed models.
© 2023 The Author(s). Published by Elsevier Inc. on behalf of American Shoulder & Elbow Surgeons. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

The term artificial intelligence (AI) was first coined by McCarthy et al in 1955 on the basis that "every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it".[52] The field has evolved dramatically over time, and more notably over the last decade. It has transformed various industries—including health care—by providing automation, efficiency, precision, accuracy, and decision-making support for simple and complex tasks.[42] The use of virtual assistants, targeted marketing, content prediction, and many other applications have become so routine in our daily lives that frequently we miss the fact that we use AI technologies every day.[42] Electronic medical records (EMRs) are an unprecedented source of medical unstructured data (ie, big data). Extracting relevant clinical data from big data is a well-recognized challenge[75,84] and AI has emerged as a useful tool to accomplish this task.[39,43,63] Despite the enormous clinical and research potential of AI, shoulder surgeons have been relatively late adopters of these technologies.[25,50] Orthopedic surgery has recently adopted AI and a variety of

Institutional review board approval was not required for this review.

*Corresponding author: John W. Sperling, MD, MBA, Department of Orthopedic Surgery, Mayo Clinic, 200 First St SW, Rochester, MN 55905, USA.
E-mail address: sperling.john@mayo.edu (J.W. Sperling).

https://doi.org/10.1016/j.xrrt.2023.07.008
2666-6391/© 2023 The Author(s). Published by Elsevier Inc. on behalf of American Shoulder & Elbow Surgeons. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

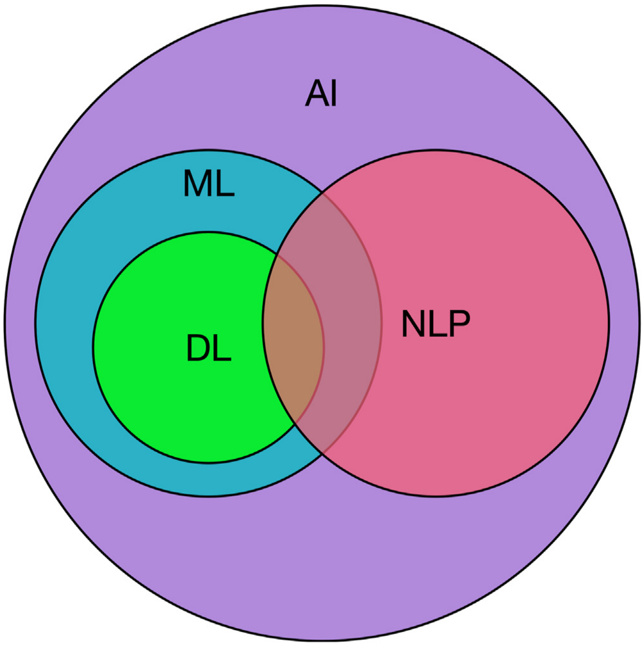

Figure 1 Interrelation of different subfields of Artificial Intelligence. *AI*, artificial intelligence; *ML*, machine learning; *DL*; deep Learning; *NLP*, Neuro-linguistic Programming.

applications have been published over the past few years.[49,62] Most of the literature available on AI in orthopedics encompasses hip and knee related studies.[39,49] A recent systematic review of AI literature related to shoulder surgery[25] found 48 articles, and their external validity is yet to be determined. Being able to understand the principles behind AI represents one of the barriers to translate these techniques into our surgical practice as well as research and education efforts. The purpose of the present review is to provide an overview of AI within orthopedics and shoulder surgery. Furthermore, we review the recent literature to explore current and forthcoming AI applications.

Artificial intelligence, machine learning and deep learning

AI encompasses every computer-performed task that simulates or improves upon human intelligence. **Machine learning (ML)** is a subcategory of AI that uses algorithms to automatically learn insights and recognize patterns from data, applying that learning to make increasingly better decisions. ML can be utilized to identify relationships between a group of variables (eg, possible risk factors) and one or more outcomes (eg, complications, revision surgery, or another dependent variables) without preconceived criteria (Fig. 1).[33] To achieve this, algorithms are created to "learn" from large data sets with known variables called training data. Next, the trained algorithm is used to suggest outcomes from unseen data (testing data). ML algorithms are referred to as "supervised" when human input is needed to label or group variables, whereas "unsupervised" ML algorithms are fed with unlabeled data and are programed to find clusters or patterns within that data.[62,63] In orthopedic surgery, most ML algorithms[62] correspond to supervised ML and focus on classification or regression (prediction) tasks. Algorithms vary widely depending on the nature of each specific task (Fig. 2). Examples of ML applications include fitting a linear regression algorithm to predict a stock price[10] or using a decision tree algorithm to learn to classify patients into different risk groups.[55] **Deep learning (DL)** is a subfield of ML in which algorithms are structured in multiple layers of complexity which allows to establish "deeper" interactions between the variables being analyzed as more layers are added (Fig. 3). These structures are usually referred to as "artificial neural networks" and have been proposed to represent how the human brain works. DL models have been developed for different tasks, such as training a convolutional neural network (CNN) to classify natural images[35] or to detect pneumonia in chest X-rays.[30] Initial uses also include programs that were designed to accept patient images for detecting pathology such as skin cancer, diabetic retinopathy, and mammographic lesions.[17,24,34] Essentially, AI allows automation of complex and tedious tasks and the understanding of complex relationships. AI will likely be implemented in many facets of health care that include Patient Evaluation, Research, Medical Education, EMR analyses, Imaging, Surgery, and Rehabilitation among many others.

Patient-specific predictions for complications, outcomes, and costs

Within routine clinic visits, physicians often gather information through evaluation of the patients' history, physical examination, and imaging prior to generating an initial (or definitive) diagnosis. After weighting the risks and benefits of possible interventions, recommendations are given to the patient that are largely based on the clinical expertise and knowledge of a particular surgeon or caregiver. Within AI, DL algorithms work similarly by establishing complex (multilayer) relationships between "predictor variables" and outcomes.[50] The ability to analyze large data sets through AI-based strategies may change the way we make every day clinical decisions by hopefully providing safer and more informed options for patients.

In shoulder surgery, advancements are being made in applying AI for patient-specific risk predictions, including predicting complications, outcomes, and costs.[2,6,13,21,31,36,37,46-48,53,60] Most recently published studies are focused on predicting perioperative complications in shoulder arthroplasty, particularly within the 30-day postoperative period.[2,6,13,14,21,31,46] In 2021, Lopez et al used 21,544 elective primary shoulder arthroplasty cases from a national database to develop and test ML models for predicting nonhome discharge and the occurrence of 1 or more postoperative complications within 30-days.[46] Similarly, Devana et al used a California database to test several ML models for predicting the occurrence of at least one major postoperative complication following primary reverse shoulder arthroplasty.[13] Certain complications have generated particular interest. For example, multiple studies have applied AI for predicting postoperative readmission.[2,13,14,21] This is especially important with the increase in outpatient shoulder arthroplasty and concomitant need for identifying optimal candidates.[6]

AI is also being increasingly explored for predicting functional outcomes, patient satisfaction, and costs following shoulder arthroplasty.[36,37,53] Kumar et al used 2153 primary anatomic total shoulder arthroplasty (TSA) and 3621 reverse arthroplasty patients to develop and test a ML model for predicting achievement of the minimal clinically important difference and substantial clinical benefit for the American Shoulder and Elbow Surgeons score, Constant Score, Global Shoulder Function score, and other functional outcomes at 2-3 years postoperatively.[36] Similarly, ML models for predicting achievement of the minimal clinically important difference and substantial clinical benefit patient satisfaction-based thresholds for active internal rotation following anatomic TSA and reverse TSA have been tested.[37] Only one study has applied AI for predicting patient satisfaction following shoulder arthroplasty.[60] This study by Polce et al tested several ML models using 413 patients for predicting patient satisfaction 2 years

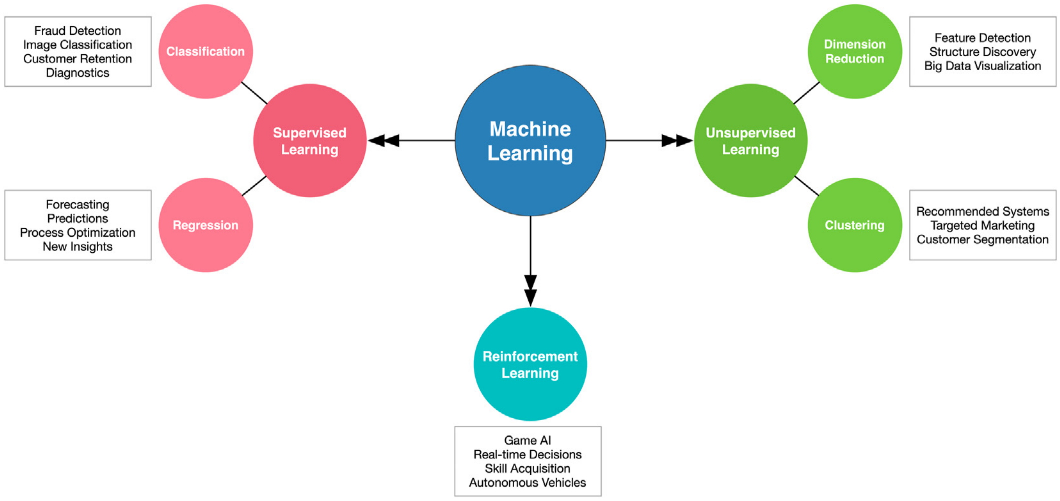

Figure 2 Machine Learning can be divided into Supervised Learning, Unsupervised Learning and Reinforcement Learning. Though Supervised Machine Learning algorithms are more frequently found in orthopedic surgery literature, each subfield has its own applications. *AI*, artificial intelligence.

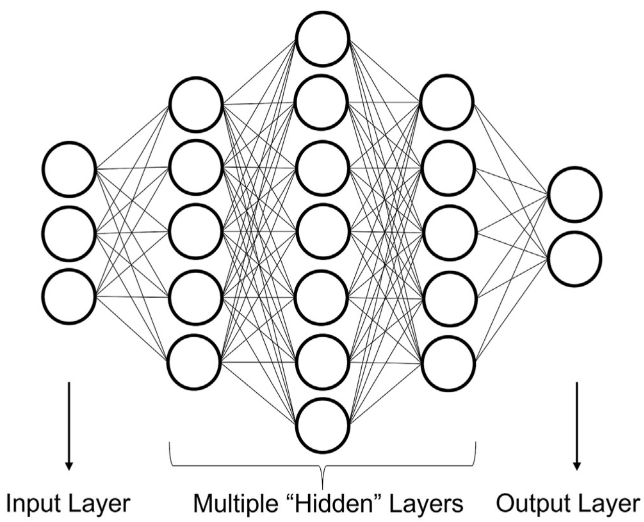

Figure 3 Scheme of an Artificial Neural Network. Input values (input layer) are processed through an interconnected network referred to as "Hidden Layers" that generate a response at the Output Layer mimicking the human brain architecture.

following primary anatomic TSA or reverse TSA.[60] In regards to costs, Karnuta et al tested AI for predicting total costs following primary shoulder arthroplasty (anatomic TSA, reverse TSA, hemiarthroplasty) using a national database with 111,147 patients.[31]

As highlighted from the aforementioned studies, these advancements are predominantly within shoulder arthroplasty. Nonetheless, patient-specific predictions are beginning to be explored in other areas of shoulder surgery, such as in rotator cuff repair (RCR) and shoulder instability, with yet very scarce published literature.[47,48] In regards to RCR, Lu et al used 33,976 patients from a New York state database to test several ML models for predicting total charges after elective outpatient RCR.[47] Likewise, in another publication by the same authors, 654 patient records from a regional database were used to test several ML models for predicting recurrence, progression to surgery after initial trial of nonoperative management, and development of symptomatic osteoarthritis following an initial shoulder instability event.[48] Thus, there remains a large gap in the literature applying AI to non-arthroplasty areas, warranting numerous additional studies that predict complications, functional scores, and other perioperative outcomes for these patients.

Collectively, these studies highlight the potential utility of AI for patient-specific decision making and value-based medicine. As such, AI may allow for development and implementation of risk-based patient-specific payment models in shoulder surgery. These types of models are being explored in other subspecialities of orthopedics, such as primary total knee arthroplasty (TKA) and total hip arthroplasty, and have shown promising results.[57,67] In the future, the availability of AI-based predictive algorithms may aid both patients and shoulder surgeons to make better and more informed decisions, and also may allow for more personalized patient care.

Computer vision for image analysis

One of the most exciting features of AI is its breadth of capabilities. While the prediction of outcomes such as complications and costs after surgery has been the most common application of AI in shoulder surgery to date, novel applications have been developed in order to 1) assist surgeons with preoperative planning and 2) help to streamline and improve efficiency of routine tasks.

In 2020, Taghizadeh et al developed an AI model capable of automatically quantifying and characterizing the level of degeneration of rotator cuff muscles from shoulder computed tomography images, including both muscle atrophy and fatty infiltration.[78] Likewise, Ro et al developed an magnetic resonance imaging (MRI) based DL framework to assist surgeons with analysis of the occupation ratio and fatty infiltration of the supraspinatus muscle during evaluation of patients with rotator cuff tears.[68] Yao et al demonstrated that DL can be used for the automated detection and classification of supraspinatus tears on T2-weighted coronal oblique MRI images.[83] Such applications of AI have the potential to improve outcomes for patients with rotator cuff tears by assisting surgeons with the analysis of decisive preoperative factors.

A recent meta-analysis found comparable performance between clinicians and AI in their ability to detect fractures, thereby demonstrating a promising technology that may be utilized in future applications.[38] In 2022, Grauhan et al generated a model that can recognize common causes of shoulder pain on radiographs, such as proximal humeral fractures, joint dislocation, periarticular calcification, osteoarthritis, osteosynthesis, and joint endoprosthesis.[22] In 2021, Rouzrokh et al[71] developed a CNN-based system to automatically measure the acetabular component inclination after total hip arthroplasty using postoperative X-rays. Similarly, Thomas et al[79] developed a CNN-based classifier to automatically classify knee osteoarthritis severity in radiographs. Rudisill et al[73] developed an AI model to predict early-onset adjacent segment degeneration following anterior cervical discectomy and fusion using demographic, clinical, and radiographic variables. AI models like these have the potential to serve as assistive devices by offering clinicians a way to prioritize worklists or providing additional safety in cases of increased demand.

AI models have been generated to assist surgeons with relatively routine tasks during preoperative evaluation and planning including those that have been developed to measure the critical shoulder angle (CSA).[54,76] The CSA is described as a manual measurement, which requires an appropriate anteroposterior Grashey radiograph.[56] While surgeons can easily perform the measurement, there remains an opportunity for an integrated AI tool to help standardize this evaluation. Shariatnia et al demonstrated that the CSA could precisely and accurately be automatically measured on shoulder anteroposterior radiographs, and that such a tool could not only make large-scale research projects feasible, but also prove valuable as a clinical application if integrated with existing clinical workflows.[76]

Within orthopedic surgery, patient registries have provided structured and organized pools of data that has led to significant improvements in clinical research.[12] Although, image analyses are often included within orthopedic registry studies, these account for limited aspects of the overall outcomes and often rely on tedious manual review. Rouzrokh et al expanded on this limitation within the orthopedic literature and sought to generate a hip and pelvic radiography registry of total hip arthroplasty patients utilizing deep-learning algorithms.[70] Specifically, authors developed an accurate series of DL algorithms that could rapidly curate and annotate total hip arthroplasty radiographs with 99.9% accuracy, 99.6% precision, and 99.5% recall.[70] This efficiency was the first step to generating a true linkage of clinical and radiographic outcomes.

Other surgical applications

Shoulder surgery may see substantial changes in the future with AI powered surgical tools. Promising developments have been reported for preoperative planning, intraoperative assistance (eg, navigation and augmented reality) and surgical education.[11,20,23,26,40] Three-dimensional (3D) preoperative planning for arthroplasty is gaining popularity as software availability grows each year.[26,45] AI may leverage efficiency through the surgical process from patient-specific and surgeon-specific planning to automated surgical feedback and intraoperative real-time assistance.[11,23,40] One study used 1.2 million CT images from 3000 patients to develop an AI preoperative planning system for hip replacement.[11] Preoperative planning DL algorithms achieved an excellent performance compared to standard manual workflow, lowering the average planning time from 185.4 ± 21.76 min to 1.86 ± 0.12 min.[11] Available preoperative planning software usually give the surgeon a default plan (manufacturer's plan). In 2017, Okada et al analyzed 45 TKA plans and found that 91.1% required manual changes by the surgeon from the original manufacturer's version.[58] Within the shoulder literature, Erickson et al warned on the limited agreement between surgeon and commercial software measurements for version, inclination, and subluxation.[16] AI strategies may help close this gap. A recent study used a dataset from 5409 TKA preoperative plans, including the manufacturer's default plan and corrected plans by 39 surgeons, to train a supervised ML model to automatically predict surgeon's corrections from the manufacturer's plan. Using this approach, the authors found a 39.7% reduction in surgeons' corrections. In the future, large high-quality databases may allow for a more accurate and customized planning.

The ability to accurately transfer the preoperative plan to the patient is crucial. Though patient-specific instrumentation guides can effectively reduce the variability from planning to patient,[29] the associated costs and delay in manufacturing prevent its use in every case. Augmented and mixed reality technology allows virtual objects to be blended and interact with the real world.[23] This technology can incorporate AI to make accurate predictions of relevant surgical landmarks on the real surgical field.[23] Sieminow et al recently assessed the feasibility of an augmented reality and artificial intelligence—assisted surgical navigation system in cadavers.[77] After acquiring a preoperative CT of each specimen, the augmented reality and artificial intelligence system accurately overlayed a 3D render of the specimen's anatomy over the surgical field to allow percutaneous instrumentation of the lumbar pedicles with a metallic probe.[77] The average time of percutaneous instrumentation of each pedicle was 38.2 seconds with excellent position of all 24 evaluated probes.[77] Such technologies may revolutionize the way we transfer our surgical plan to patients, lowering surgical times and eventually resulting in a better care for patients.

Surgical education is another area with an enormous potential for AI-driven strategies. Several AI-driven developments have been reported with the potential to provide customized performance assessment and feedback to surgical trainees with minimal or no supervision from surgical educators.[23] Virtual reality (VR) training has shown to improve efficiency, reduce error rate and improve tissue handling in surgical trainees.[61] One study performed in sawbones that compared VR based training with standard surgical education for tibial intramedullary nailing, found significantly higher knowledge of instruments, steps completed, and overall performance in the VR trained group.[7] Surgical mentoring may also be AI assisted in the near future. ML powered tools can accurately distinguish the surgical expertise of an individual or grade a basic surgical skills test without the direct assessment of an expert.[4,82] Recently a Delphi consensus that included surgeons (42.5%), engineers/technical AI experts (27.5%), and other professionals (30%), reported the foreseen deliverables for surgical education in the next 10 years which are summarized in Table I.[81] While encouraging these future advances are still in their early stages. External validation and good quality studies (eg, randomized controlled trials) are mandatory to allow a successful and responsible transfer of these technologies to clinical practice and surgical education.

Evaluation of clinical outcomes

Standard outcome evaluation is performed in an episodic fashion in which the surgeon picks certain follow-up dates to take a "snapshot" of the patient's status. In order to obtain data for clinical and/or research purposes from this process, prospective data collection is required. Prospective clinical data collection is time consuming and requires relatively qualified personnel to obtain and record data properly. Institutional and national registries represent a partial solution to avoid the loss of valuable clinical information for selected conditions (ie, arthroplasty).[12] Unfortunately, the maintenance of institutional and national registries requires substantial resources.[12,72] Moreover, registry-based studies have their own limitations, usually including variable quality of the collected data, limited clinical information, and a lack of active follow-up, among others.[72] Future technologies in combination with AI powered strategies may enable resource optimization and continuous monitoring of patients.[18,49,66]

Table I
Future applications of artificial intelligence methods and artificial intelligence-enabled metrics for surgical education defined by a Delphi Consensus Panel.

Deliverable	Time frame (y)
Recognize anatomy in images from videos of the surgical field	2
Provide performance feedback to surgeon immediately after the operation	2
Identify parts of the operation on which the surgeon needs feedback	5
Overlay images to display surrounding anatomy	5
Guide surgeons on optimal use of instruments/devices	5
Enable intraoperative navigability using video, kinematics, and other imaging data for multiple procedures	10
Detect intraoperative error	10
Provide guidance on the next best step to address an intraoperative error or complication	10

The table shows possible future deliverables using AI for surgical education obtained by a Delphi Consensus Panel. All shown deliverables had at least 82.5% of consensus among experts. Adapted from Vedula et al.[81]
AI, artificial intelligence.

Digital health initiatives, and specifically Mobile Health (mHealth) technology allow real-time feedback from patients on a larger scale and will eventually change the way we follow-up patients and measure outcomes.[15,27,65,66] Current mobile devices have built-in sensors (ie, accelerometer, gyroscope, and magnetometer) that can passively store tremendous amount of data for further processing to obtain relevant clinical information.[15,64] Despite over 350,000 health/fitness/medical apps currently available,[1] most of them work in isolation making it impossible to integrate and analyze data across different systems which has prevented the ability to scale their potential in research and clinical practice.[18,66] Ramkumar et al described the valuable opportunity for orthopedic surgery behind open architecture software mHealth technology.[66] Open architecture allows data interconnection and use in ways other than originally implemented or intended.[18] Though privacy is a reasonable and foreseeable concern, there are already experiences implementing such software in compliance with the Health Insurance Portability and Accountability Act.[28,65] Apart from smart devices, braces and sleeves have technology that allows continuous patient monitoring in their daily living and/or sports activity.[32,44] One example is the motusBASEBALL sleeve (Motus Global Inc., Massapequa, NY, USA) that houses a small inertial measurement unit that allows measuring throw counts, peak elbow varus torque, arm speed, arm slot, maximum shoulder rotation, and workload.[19,41] AI algorithms may analyze wearable sensor data to monitor postoperative recovery, stablish personalized workloads, report injuries, and prevent complications among other functions.

Within shoulder surgery, Ramkumar et al described an open architecture software capable of passively measuring shoulder range of motion using a wearable smart device (watch or phone) with only 5 degrees of variability compared to a standard goniometer measurement.[64] The authors trained a DL model to decode the signal from the mobile device and transform it in a range of motion measurement of either abduction, forward flexion, external rotation, or internal rotation.[64] Furthermore, supervised ML has been found to successfully monitor and assess adherence of physiotherapy protocols post shoulder surgery using a commercially available smart watch.[9] Applying a similar strategy in a cohort of postoperative TKA patients another study showed that functional results (Patient Reported Outcomes) at 6 weeks can be predicted as early as at 11 days by analyzing wearable sensors data through ML algorithms.[5] The construction of Patient Reported Outcomes themselves may also see significant changes in the future. Recently published, the Smart Shoulder Score is the first orthopedic clinical outcome measure constructed using ML.[69] The Smart Shoulder Score was developed using a ML based strategy to identify the most predictive preoperative inputs that influence postoperative TSA outcomes, and was found to have equal or better validity, responsiveness, and clinical interpretability than other historical assessment tools.[69]

Large-scale language models

Large-Scale Language Models (LLMs) systems are able to produce language based on algorithms that incorporate the frequency by which words are associated with each other.[8] They have been in the spotlight recently in relation with a chatbot launched in November 2022 called Chat Generative Pre-Trained Transformer (ChatGPT; OpenAI, San Francisco, CA, USA).[59] This AI chatbot can provide detailed responses and answers across multiple domains of knowledge. On one hand, these types of AI applications have the potential to correctly answer many scientific questions[80]; eg, ChatGPT 4 was reported to pass the United States Medical Licensing Exam.[3] On the other hand, the information produced by LLM systems is not always the truth. LLM could potentially be used to automate letters to patients or notes in the EMR. There is a lot of controversy about its use in the creation of scientific publications, and recently the Journal of Shoulder and Elbow Surgery (amongst other Journals) published a policy in that regard.[74] Some countries have banned the use of certain chatbots until they are validated, but standards for validation of LLM for each area of knowledge will be challenging to develop.[51,80]

Conclusions

AI is an expanding field with the potential for broad clinical and research applications in orthopedic surgery. Decision-making, image evaluation, surgical planning and patient follow-up are some of the current areas of development with enormous opportunities for clinical practice and future research. Many challenges still need to be addressed to fully leverage the potential of AI to clinical practice and research such as privacy issues, data ownership, and external validation of the proposed models. AI tools are as good as the data that they are trained on which highlights the importance of maintaining high quality clinical and image registries to allow meaningful AI-derived insights from big data analysis. Currently, most of the shoulder literature related to AI focuses on shoulder arthroplasty with much to be explored for shoulder instability, RCR, and other shoulder conditions.

Disclaimers:

Funding: No funding was disclosed by the authors.
Conflicts of interest: The authors, their immediate families, and any research foundation with which they are affiliated have not

received any financial payments or other benefits from any commercial entity related to the subject of this article.

References

1. Aitken M, Nass D. Digital health trends 2021. IQVIA Institute for Human Data Science; 2021.
2. Arvind V, London DA, Cirino C, Keswani A, Cagle PJ. Comparison of machine learning techniques to predict unplanned readmission following total shoulder arthroplasty. J Shoulder Elbow Surg 2021;30:e50-9. https://doi.org/10.1016/j.jse.2020.05.013.
3. Ault A. AI bot ChatGPT passes US medical licensing exams without cramming – unlike students. Available at: https://www.medscape.com/viewarticle/987549. Accessed April 21, 2023.
4. Belmar F, Gaete MI, Escalona G, Carnier M, Duran V, Villagran I, et al. Artificial intelligence in laparoscopic simulation: a promising future for large-scale automated evaluations. Surg Endosc 2022;37:4942-6. https://doi.org/10.1007/s00464-022-09576-1.
5. Bini SA, Shah RF, Bendich I, Patterson JT, Hwang KM, Zaid MB. Machine learning algorithms can use wearable sensor data to accurately predict six-week patient-reported outcome scores following joint replacement in a prospective trial. J Arthroplasty 2019;34:2242-7. https://doi.org/10.1016/j.arth.2019.07.024.
6. Biron DR, Sinha I, Kleiner JE, Aluthge DP, Goodman AD, Sarkar IN, et al. A Novel machine learning model developed to assist in patient selection for outpatient total shoulder arthroplasty. J Am Acad Orthop Surg 2020;28:e580-5. https://doi.org/10.5435/JAAOS-D-19-00395.
7. Blumstein G, Zukotynski B, Cevallos N, Ishmael C, Zoller S, Burke Z, et al. Randomized trial of a virtual reality tool to teach surgical technique for tibial shaft fracture intramedullary nailing. J Surg Educ 2020;77:969-77. https://doi.org/10.1016/j.jsurg.2020.01.002.
8. Brown T, Mann B, Ryder N, Subbiah M, Kaplan JD, Dhariwal P, et al. Language models are few-shot learners. Adv Neural Inf Process Syst 2020;33:1877-901. https://doi.org/10.48550/arXiv.2005.14165.
9. Burns DM, Leung N, Hardisty M, Whyne CM, Henry P, McLachlin S. Shoulder physiotherapy exercise recognition: machine learning the inertial signals from a smartwatch. Physiol Meas 2018;39:075007. https://doi.org/10.1088/1361-6579/aacfd9.
10. Cakra YE, Trisedya BD. Stock price prediction using linear regression based on sentiment analysis. In: 2015 International conference on Advanced Computer Science and Information Systems (ICACSIS); 2015. p. 147-54. https://doi.org/10.1109/ICACSIS.2015.7415179.
11. Chen X, Liu X, Wang Y, Ma R, Zhu S, Li S, et al. Development and validation of an artificial intelligence preoperative planning system for total hip arthroplasty. Front Med 2022;9:841202. https://doi.org/10.3389/fmed.2022.841202.
12. Delaunay C. Registries in orthopaedics. Orthop Traumatol Surg Res 2015;101:S69-75. https://doi.org/10.1016/j.otsr.2014.06.029.
13. Devana SK, Shah AA, Lee C, Gudapati V, Jensen AR, Cheung E, et al. Development of a machine learning algorithm for prediction of complications and unplanned readmission following reverse total shoulder arthroplasty. SAGE Publications Inc J Shoulder Elb Arthroplast 2021;5:24715492211038172. https://doi.org/10.1177/24715492211038172.
14. Devana SK, Shah AA, Lee C, Jensen AR, Cheung E, van der Schaar M, et al. Development of a machine learning algorithm for prediction of complications and unplanned readmission following primary anatomic total shoulder replacements. J Shoulder Elb Arthroplast 2022;6:24715492221075444. https://doi.org/10.1177/24715492221075444.
15. Dobkin BH, Dorsch A. The promise of mHealth: daily activity monitoring and outcome assessments by wearable sensors. Neurorehabil Neural Repair 2011;25:788-98. https://doi.org/10.1177/1545968311425908.
16. Erickson BJ, Chalmers PN, Denard P, Lederman E, Horneff G, Werner BC, et al. Does commercially available shoulder arthroplasty preoperative planning software agree with surgeon measurements of version, inclination, and subluxation? J Shoulder Elbow Surg 2021;30:413-20. https://doi.org/10.1016/j.jse.2020.05.027.
17. Esteva A, Kuprel B, Novoa RA, Ko J, Swetter SM, Blau HM, et al. Dermatologist-level classification of skin cancer with deep neural networks. Nature 2017;542:115-8. https://doi.org/10.1038/nature21056.
18. Estrin D, Sim I. Open mHealth architecture: an engine for health care innovation. Science 2010;330:759-60. https://doi.org/10.1126/science.1196187.
19. Fury MS, Oh LS, Berkson EM. New opportunities in assessing return to performance in the elite athlete: unifying sports medicine, data analytics, and sports science. Arthrosc Sports Med Rehabil 2022;4:e1897-902. https://doi.org/10.1016/j.asmr.2022.08.001.
20. Ghaednia H, Fourman MS, Lans A, Detels K, Dijkstra H, Lloyd S, et al. Augmented and virtual reality in spine surgery, current applications and future potentials. Spine J 2021;21:1617-25. https://doi.org/10.1016/j.spinee.2021.03.018.
21. Gowd AK, Agarwalla A, Amin NH, Romeo AA, Nicholson GP, Verma NN, et al. Construct validation of machine learning in the prediction of short-term postoperative complications following total shoulder arthroplasty. J Shoulder Elbow Surg 2019;28:e410-21. https://doi.org/10.1016/j.jse.2019.05.017.
22. Grauhan NF, Niehues SM, Gaudin RA, Keller S, Vahldiek JL, Adams LC, et al. Deep learning for accurately recognizing common causes of shoulder pain on radiographs. Skeletal Radiol 2022;51:355-62. https://doi.org/10.1007/s00256-021-03740-9.
23. Guerrero DT, Asaad M, Rajesh A, Hassan A, Butler CE. Advancing surgical education: the use of artificial intelligence in surgical training. Am Surg 2023;89:49-54. https://doi.org/10.1177/00031348221101503.
24. Gulshan V, Peng L, Coram M, Stumpe MC, Wu D, Narayanaswamy A, et al. Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. JAMA 2016;316:2402-10. https://doi.org/10.1001/jama.2016.17216.
25. Gupta P, Haeberle HS, Zimmer ZR, Levine WN, Williams RJ, Ramkumar PN. Artificial intelligence-based applications in shoulder surgery leaves much to be desired: a systematic review. JSES Rev Rep Tech 2023;3:189-200. https://doi.org/10.1016/j.xrrt.2022.12.006.
26. Hall T, Wong JRY, Dirckx M, Rajesparan K, Rashid A. Pre-operative arthritic glenoid assessment: 3D automated planning software versus manual multi-planar measurements of version and inclination. J Orthop 2023;36:24-8. https://doi.org/10.1016/j.jor.2022.12.005.
27. Han D, Ding EY, Cho C, Jung H, Dickson EL, Mohagheghian F, et al. A smartwatch system for continuous monitoring of atrial fibrillation in older adults after stroke or transient ischemic attack: application design study. JMIR Cardio 2023;7:e41691. https://doi.org/10.2196/41691.
28. Harned M, Dhami M, Reger GM. Evaluation of a psychoeducational group to expand mobile application knowledge and use in a veteran residential treatment program. J Technol Behav Sci 2023;8:118-27. https://doi.org/10.1007/s41347-023-00299-1.
29. Iannotti JP, Davidson IU, Ricchetti ET. Three-dimensional preoperative planning and patient-specific instrumentation for total shoulder arthroplasty. Semin Arthroplasty 2017;28:25-9. https://doi.org/10.1053/j.sart.2017.05.005.
30. Jaiswal AK, Tiwari P, Kumar S, Gupta D, Khanna A, Rodrigues JJPC. Identifying pneumonia in chest X-rays: a deep learning approach. Measurement 2019;145:511-8. https://doi.org/10.1016/j.measurement.2019.05.076.
31. Karnuta JM, Churchill JL, Haeberle HS, Nwachukwu BU, Taylor SA, Ricchetti ET, et al. The value of artificial neural networks for predicting length of stay, discharge disposition, and inpatient costs after anatomic and reverse shoulder arthroplasty. J Shoulder Elbow Surg 2020;29:2385-94. https://doi.org/10.1016/j.jse.2020.04.009.
32. Kim H, Lee K, Jo G, Kim J-S, Lim MT, Cha Y. Tendon-inspired piezoelectric sensor for biometric application. IEEE ASME Trans Mechatron 2021;26:2538-47. https://doi.org/10.1109/tmech.2020.3041877.
33. Ko S, Pareek A, Ro DH, Lu Y, Camp CL, Martin RK, et al. Artificial intelligence in orthopedics: three strategies for deep learning with orthopedic specific imaging. Knee Surg Sports Traumatol Arthrosc 2022;30:758-61. https://doi.org/10.1007/s00167-021-06838-8.
34. Kooi T, Litjens G, van Ginneken B, Gubern-Mérida A, Sánchez CI, Mann R, et al. Large scale deep learning for computer aided detection of mammographic lesions. Med Image Anal 2017;35:303-12. https://doi.org/10.1016/j.media.2016.07.007.
35. Krizhevsky A, Sutskever I, Hinton GE. ImageNet classification with deep convolutional neural networks. Commun ACM 2017;60:84-90. https://doi.org/10.1145/3065386.
36. Kumar V, Roche C, Overman S, Simovitch R, Flurin P-H, Wright T, et al. Using machine learning to predict clinical outcomes after shoulder arthroplasty with a minimal feature set. J Shoulder Elbow Surg 2021;30:e225-36. https://doi.org/10.1016/j.jse.2020.07.042.
37. Kumar V, Schoch BS, Allen C, Overman S, Teredesai A, Aibinder W, et al. Using machine learning to predict internal rotation after anatomic and reverse total shoulder arthroplasty. J Shoulder Elbow Surg 2022;31:e234-45. https://doi.org/10.1016/j.jse.2021.10.032.
38. Kuo RYL, Harrison C, Curran TA, Jones B, Freethy A, Cussons D, et al. Artificial intelligence in fracture detection: a systematic review and meta-analysis. Radiology 2022;304:50-62. https://doi.org/10.1148/radiol.211785.
39. Kurmis AP, Ianunzio JR. Artificial intelligence in orthopedic surgery: evolution, current state and future directions. Arthroplasty 2022;4:9. https://doi.org/10.1186/s42836-022-00112-z.
40. Lambrechts A, Wirix-Speetjens R, Maes F, Van Huffel S. Artificial intelligence based patient-specific preoperative planning algorithm for total knee arthroplasty. Front Robot AI 2022;9:840282. https://doi.org/10.3389/frobt.2022.840282.
41. Leafblad ND, Larson DR, Fleisig GS, Conte S, Fealy SA, Dines JS, et al. Variability in baseball throwing metrics during a structured long-toss program: does one size fit all or should programs be individualized? Sports Health 2019;11:535-42. https://doi.org/10.1177/1941738119869945.
42. Lee RS. Artificial intelligence in daily life. Nature, Singapore.: Springer; 2020. https://doi.org/10.1007/978-981-15-7695-9.
43. Li C, Alike Y, Hou J, Long Y, Zheng Z, Meng K, et al. Machine learning model successfully identifies important clinical features for predicting outpatients with rotator cuff tears. Knee Surg Sports Traumatol Arthrosc 2023;31:2615-23. https://doi.org/10.1007/s00167-022-07298-4.
44. Li RT, Kling SR, Salata MJ, Cupp SA, Sheehan J, Voos JE. Wearable performance devices in sports medicine. Sports Health 2016;8:74-8. https://doi.org/10.1177/1941738115616917.

45. Lilley BM, Lachance A, Peebles AM, Powell SN, Romeo AA, Denard PJ, et al. What is the deviation in 3D preoperative planning software? A systematic review of concordance between plan and actual implant in reverse total shoulder arthroplasty. J Shoulder Elbow Surg 2022;31:1073-82. https://doi.org/10.1016/j.jse.2021.12.006.
46. Lopez CD, Constant M, Anderson MJJ, Confino JE, Heffernan JT, Jobin CM. Using machine learning methods to predict nonhome discharge after elective total shoulder arthroplasty. JSES Int 2021;5:692-8. https://doi.org/10.1016/j.jseint.2021.02.011.
47. Lu Y, Labott JR, Salmons Iv HI, Gross BD, Barlow JD, Sanchez-Sotelo J, et al. Identifying modifiable and nonmodifiable cost drivers of ambulatory rotator cuff repair: a machine learning analysis. J Shoulder Elbow Surg 2022;31:2262-73. https://doi.org/10.1016/j.jse.2022.04.008.
48. Lu Y, Pareek A, Wilbur RR, Leland DP, Krych AJ, Camp CL. Understanding anterior shoulder instability through machine learning: new models that predict recurrence, progression to surgery, and development of arthritis. Orthop J Sports Med 2021;9:23259671211053326. https://doi.org/10.1177/23259671211053326.
49. Makhni EC, Makhni S, Ramkumar PN. Artificial intelligence for the orthopaedic surgeon: an overview of potential benefits, limitations, and clinical applications. J Am Acad Orthop Surg 2021;29:235-43. https://doi.org/10.5435/JAAOS-D-20-00846.
50. Martin RK, Ley C, Pareek A, Groll A, Tischer T, Seil R. Artificial intelligence and machine learning: an introduction for orthopaedic surgeons. Knee Surg Sports Traumatol Arthrosc 2022;30:361-4. https://doi.org/10.1007/s00167-021-06741-2.
51. Martindale J. These are the countries where ChatGPT is currently banned. Available at: https://www.digitaltrends.com/computing/these-countries-chatgpt-banned/. Accessed April 21, 2023.
52. McCarthy J, Minsky ML, Rochester N, Shannon CE. A proposal for the dartmouth summer research project on artificial intelligence, August 31, 1955. AI Mag 2006;27:12. https://doi.org/10.1609/aimag.v27i4.1904.
53. McLendon PB, Christmas KN, Simon P, Plummer OR, Hunt A, Ahmed AS, et al. Machine learning can predict level of improvement in shoulder arthroplasty. JB JS Open Access 2021;6:e20.00128. https://doi.org/10.2106/JBJS.OA.20.00128.
54. Minelli M, Cina A, Galbusera F, Castagna A, Savevski V, Sconfienza LM. Measuring the critical shoulder angle on radiographs: an accurate and repeatable deep learning model. Skeletal Radiol 2022;51:1873-8. https://doi.org/10.1007/s00256-022-04041-5.
55. Moon M, Lee SK. Applying of decision tree analysis to risk factors associated with pressure ulcers in long-term care facilities. Healthc Inform Res 2017;23:43-52. https://doi.org/10.4258/hir.2017.23.1.43.
56. Moor BK, Bouaicha S, Rothenfluh DA, Sukthankar A, Gerber C. Is there an association between the individual anatomy of the scapula and the development of rotator cuff tears or osteoarthritis of the glenohumeral joint?: A radiological study of the critical shoulder angle. Bone Joint J 2013;95-b:935-41. https://doi.org/10.1302/0301-620x.95b7.31028.
57. Navarro SM, Wang EY, Haeberle HS, Mont MA, Krebs VE, Patterson BM, et al. Machine learning and primary total knee arthroplasty: patient forecasting for a patient-specific payment model. J Arthroplasty 2018;33:3617-23. https://doi.org/10.1016/j.arth.2018.08.028.
58. Okada Y, Teramoto A, Suzuki T, Kii Y, Watanabe K, Yamashita T. Preoperative corrections are required for planning of patient-specific instrumentation in total knee arthroplasty. Knee 2017;24:1492-7. https://doi.org/10.1016/j.knee.2017.09.008.
59. OpenAI. ChatGPT. Available from: https://openai.com/blog/chatgpt. Accessed April 21, 2023.
60. Polce EM, Kunze KN, Fu MC, Garrigues GE, Forsythe B, Nicholson GP, et al. Development of supervised machine learning algorithms for prediction of satisfaction at 2 years following total shoulder arthroplasty. J Shoulder Elbow Surg 2021;30:e290-9. https://doi.org/10.1016/j.jse.2020.09.007.
61. Portelli M, Bianco SF, Bezzina T, Abela JE. Virtual reality training compared with apprenticeship training in laparoscopic surgery: a meta-analysis. Ann R Coll Surg Engl 2020;102:672-84. https://doi.org/10.1308/rcsann.2020.0178.
62. Pruneski JA, Pareek A, Kunze KN, Martin RK, Karlsson J, Oeding JF, et al. Supervised machine learning and associated algorithms: applications in orthopedic surgery. Knee Surg Sports Traumatol Arthrosc 2022;31:1196-202. https://doi.org/10.1007/s00167-022-07181-2.
63. Pruneski JA, Williams RJ 3rd, Nwachukwu BU, Ramkumar PN, Kiapour AM, Martin RK, et al. The development and deployment of machine learning models. Knee Surg Sports Traumatol Arthrosc 2022;30:3917-23. https://doi.org/10.1007/s00167-022-07155-4.
64. Ramkumar PN, Haeberle HS, Navarro SM, Sultan AA, Mont MA, Ricchetti ET, et al. Mobile technology and telemedicine for shoulder range of motion: validation of a motion-based machine-learning software development kit. J Shoulder Elbow Surg 2018;27:1198-204. https://doi.org/10.1016/j.jse.2018.01.013.
65. Ramkumar PN, Haeberle HS, Ramanathan D, Cantrell WA, Navarro SM, Mont MA, et al. Remote patient monitoring using mobile health for total knee arthroplasty: validation of a wearable and machine learning-based surveillance platform. J Arthroplasty 2019;34:2253-9. https://doi.org/10.1016/j.arth.2019.05.021.
66. Ramkumar PN, Muschler GF, Spindler KP, Harris JD, McCulloch PC, Mont MA. Open mHealth architecture: a primer for tomorrow's orthopedic surgeon and introduction to its use in lower extremity arthroplasty. J Arthroplasty 2017;32:1058-62. https://doi.org/10.1016/j.arth.2016.11.019.
67. Ramkumar PN, Navarro SM, Haeberle HS, Karnuta JM, Mont MA, Iannotti JP, et al. Development and validation of a machine learning algorithm after primary total hip arthroplasty: applications to length of stay and payment models. J Arthroplasty 2019;34:632-7. https://doi.org/10.1016/j.arth.2018.12.030.
68. Ro K, Kim JY, Park H, Cho BH, Kim IY, Shim SB, et al. Deep-learning framework and computer assisted fatty infiltration analysis for the supraspinatus muscle in MRI. Sci Rep 2021;11, 15065. https://doi.org/10.1038/s41598-021-93026-w.
69. Roche C, Kumar V, Overman S, Simovitch R, Flurin PH, Wright T, et al. Validation of a machine learning-derived clinical metric to quantify outcomes after total shoulder arthroplasty. J Shoulder Elbow Surg 2021;30:2211-24. https://doi.org/10.1016/j.jse.2021.01.021.
70. Rouzrokh P, Khosravi B, Johnson QJ, Faghani S, Vera Garcia DV, Erickson BJ, et al. Applying deep learning to establish a total hip arthroplasty radiography registry: a stepwise approach. J Bone Joint Surg Am 2022;104:1649-58. https://doi.org/10.2106/jbjs.21.01229.
71. Rouzrokh P, Wyles CC, Philbrick KA, Ramazanian T, Weston AD, Cai JC, et al. A deep learning tool for automated radiographic measurement of acetabular component inclination and version after total hip arthroplasty. J Arthroplasty 2021;36:2510-2517.e6. https://doi.org/10.1016/j.arth.2021.02.026.
72. Rubinger L, Ekhtiari S, Gazendam A, Bhandari M. Registries: big data, bigger problems? Injury 2021;54(Suppl 3):S39-42. https://doi.org/10.1016/j.injury.2021.12.016.
73. Rudisill SS, Hornung AL, Barajas JN, Bridge JJ, Mallow GM, Lopez W, et al. Artificial intelligence in predicting early-onset adjacent segment degeneration following anterior cervical discectomy and fusion. Eur Spine J 2022;31:2104-14. https://doi.org/10.1007/s00586-022-07238-3.
74. Sanchez-Sotelo J, Jed Kuhn JE, Mallon WJ. Artificial intelligence and the creation of scientific papers. J Shoulder Elbow Surg 2023;32:685-6. https://doi.org/10.1016/j.jse.2023.02.002.
75. Schilling PL, Bozic KJ. The big to do about "big data". Clin Orthop Relat Res 2014;472:3270-2. https://doi.org/10.1007/s11999-014-3887-0.
76. Shariatnia MM, Ramazanian T, Sanchez-Sotelo J, Maradit Kremers H. Deep learning model for measurement of shoulder critical angle and acromion index on shoulder radiographs. JSES Rev Rep Tech 2022;2:297-301. https://doi.org/10.1016/j.xrrt.2022.03.002.
77. Siemionow KB, Katchko KM, Lewicki P, Luciano CJ. Augmented reality and artificial intelligence-assisted surgical navigation: technique and cadaveric feasibility study. J Craniovertebr Junction Spine 2020;11:81-5. https://doi.org/10.4103/jcvjs.JCVJS_48_20.
78. Taghizadeh E, Truffer O, Becce F, Eminian S, Gidoin S, Terrier A, et al. Deep learning for the rapid automatic quantification and characterization of rotator cuff muscle degeneration from shoulder CT datasets. Eur Radiol 2021;31:181-90. https://doi.org/10.1007/s00330-020-07070-7.
79. Thomas KA, Kidzinski L, Halilaj E, Fleming SL, Venkataraman GR, Oei EHG, et al. Automated classification of radiographic knee osteoarthritis severity using deep neural networks. Radiol Artif Intell 2020;2:e190065. https://doi.org/10.1148/ryai.2020190065.
80. Van Noorden R. How language-generation AIs could transform science. Nature 2022;605:21. https://doi.org/10.1038/d41586-022-01191-3.
81. Vedula SS, Ghazi A, Collins JW, Pugh C, Stefanidis D, Meireles O, et al. Artificial intelligence methods and artificial intelligence-enabled metrics for surgical education: a multidisciplinary consensus. J Am Coll Surg 2022;234:1181-92. https://doi.org/10.1097/XCS.0000000000000190.
82. Winkler-Schwartz A, Yilmaz R, Mirchi N, Bissonnette V, Ledwos N, Siyar S, et al. Machine learning identification of surgical and operative factors associated with surgical expertise in virtual reality simulation. JAMA Netw Open 2019;2:e198363. https://doi.org/10.1001/jamanetworkopen.2019.8363.
83. Yao J, Chepelev L, Nisha Y, Sathiadoss P, Rybicki FJ, Sheikh AM. Evaluation of a deep learning method for the automated detection of supraspinatus tears on MRI. Skeletal Radiol 2022;51:1765-75. https://doi.org/10.1007/s00256-022-04008-6.
84. Ye M, Zhang H, Li L. Research on data mining application of orthopedic rehabilitation information for smart medical. IEEE Access 2019;7:177137-47. https://doi.org/10.1109/access.2019.2957579.